Comparing Different COVID-19 Vaccine Allocation Strategies in the Rohingya Refugee Camps in Bangladesh

A research on the dynamics between vaccine prioritization, COVID-19 infections and economic interactions between refugees and host communities

By Felix Wilbrink
August 2021

A Master Thesis Engineering & Policy Analysis

A STUDY ON COMPARING DIFFERENT COVID-19 VACCINE ALLOCATION STRATEGIES IN THE ROHINGYA REFUGEE CAMPS IN BANGLADESH

A thesis submitted to the Delft University of Technology in partial fulfillment
of the requirements for the degree of

Master of Science Engineering & Policy Analysis

by

Felix Wilbrink

Publicly defended on
August 30th 2021

Felix Wilbrink: *A Study on Comparing Different COVID-19 Vaccine Allocation Strategies in the Rohingya Refugee Camps in Bangladesh* (2021)

For the model, visit:
https://github.com/felixwilbrink/thesis.git

The work in this thesis was made for:

TU Delft

MSc Engineering & Policy Analysis
Faculty of Technology, Policy & Management
Delft University of Technology

Supervisors: Prof.dr. T.C. (Tina) Comes
Prof.dr. M.E. (Martijn) Warnier

ACKNOWLEDGEMENTS

Since I was a little boy, me and my sister had sleep overs at my granddad's house. Since those days, my *opa René* always takes very good care of us: we go swimming together in the morning, visit museums in the afternoon, joke around with *buurman Wim* and we eat *"bolletjes met worst"*. The days we have spent with our granddad reflects our privileged live of growing up in a country which is safe, rich and full of opportunities. For example, the opportunity of finishing a master degree by handing-in this thesis.

In opa René's house, we are never alone. Since I can remember, my granddad dedicates his house to host people from all over the world: from Iran, China, Cameroon, Somalia, anywhere you can imagine. Most of these people are refugees, who were forced to flee their country of birth as is not as safe and developed as our country. To help these people integrate, my granddad has made it a daily habit to teach them the Dutch language, make sure they have access to their basic needs and learn them our basic norms and values. But life has changed in the last year, as we were all forced to live up with the harsh conditions of COVID-19. For me, the quite unsocial and isolated process of writing a thesis was even further increased. I could not study with my fellow study friends and there was no chance of meeting my supervisors in real-life. Also for my granddad life was isolated, as he could not offer his help to others which he loves so much.

However, at the time of writing these words, COVID-19 vaccines are finally creating more freedom for both my granddad and myself. Both me and my granddad have been vaccinated against COVID-19, making it possible for me to present my thesis in real-life instead of an online *Zoom-meeting*; my granddad can finally organize his teaching classes again. But still, we are quite privileged to be one of the first to have access to vaccines as a solution to bring back our normal lives. As access to vaccines for people in refugee camps is not so certain, I decided to write my thesis on a topic which is related to COVID-19 vaccines and how these can be used to help people in need. COVID-19 is a very up-to-date and urgent problem, which is most reflected by its impact vulnerable people such as refugees. Choosing this topic, I hope to contribute and be part of the help we can offer to people with smaller chances in life than myself.

I would like to express my thanks to a few people, as they have inspired or helped me to guide me through the writing of my thesis. First of all, thanks to Opa René as he has inspired me with his tireless efforts to help out people in need. Secondly, thanks to my supervisors Tina and Martijn, who have helped me to structure, narrow-down and define my work with their critical and informative feed-back. Thirdly, thanks to my lovely parents Maurice & Willemijn and my sister Juno who have supported me unconditionally during my studies and have offered me the chances in life needed to be a good person. Fourthly, thanks to my beautiful girlfriend Sarawitia who has embraced and supported me a lot during the bumpy and struggling ride of writing a thesis. Lastly, thanks to my friend Max, my two fellow Theodores Daniël & Sebastian and study flatmates Boaz, Kalkie, Jits, Tjalie, Rian & Tim as they offered me lots of desirable distraction and fun in *"deze gekke tijden"*.

Enjoy my thesis!

Felix Wilbrink

EXECUTIVE SUMMARY

The novel coronavirus epidemic (also known as *COVID-19*) has spread across the globe, infecting millions of people and taking the lives of over 4 million people. From 8 billion people worldwide, an approximate 80 million people are refugees or other forcibly displaced people. As a result of ongoing political conflicts, violations and discrimination, these people were forced to leave their home countries and are one of the most vulnerable populations in the world [UNHCR, 2021a].

Although every person can be infected by COVID-19, gaps between the rich and the poor have widened since the World Health Organization (WHO) declared COVID-19 as a global pandemic. As one of the poorest, refugees do not only face the health-related challenges, but are also faced with economic and social challenges which are linked to the pandemic [Goolsbee and Syverson, 2021]. Since the start of COVID-19, economies and health systems were highly pressured, and for many children education was limited for months. For underdeveloped countries, which host over 80% of the total population of refugees, these disruptions were most significantly visible [UNHCR, 2021a]. One of the main priorities for these countries is to make up for the losses which were caused by the devastating impact of COVID-19. This requires the provision of adequate assistance on health, economic *and* social related challenges.

One of the biggest refugee populations in the world are the Rohingya refugees in Bangladesh. Driven by many different conflicts over the past decades, up to 1 million Rohingyas are now hosted in refugee camps. Here, the Bangladesh Government in cooperation with different humanitarian aid organizations work on several projects in order to provide the vulnerable Rohingyas with humanitarian aid assistance [UNHCR, 2020a]. But apart from their high reliance on external aid, Rohingyas have also become more active in creating livelihood-generating activities by themselves, many times in close cooperation with host communities. Over the past decades, small economies have emerged inside and around the camp settlements. Here, both populations have raised small businesses, trade goods at local markets and lend services to each other. As a result, living conditions for both the Rohingyas and host communities have improved: income-security has improved, access to water, food and other essentials is more stabilized and self-reliance has grown [Filipski et al., 2020].

However, COVID-19 has posed new challenges on the Rohingya population. Namely, several contact reducing measures were implemented by the Government of Bangladesh, such as (partial) lockdowns and in-camp movement restrictions [IDC, 2020]. Although these measures are proven to be an effective policy instrument to limit contacts between people, and therefore controlling the spread of COVID-19 [Grauer et al., 2020], they also cut off all economic dependencies among Rohingyas and with host communities. As a result, sources of daily income-generation were limited for months causing a growth in their reliance on external aid for the first time in years [Kamal et al., 2020; Bukuluki et al., 2020].

This shows, the high vulnerability of Rohingya refugees can be highlighted through different dimensions. Health-wise, implementing far-reaching measures for minimizing risks of getting infected by COVID-19 might be effective. But keeping the camps in isolation for months, other challenges emerge regarding economic problems, mental health and education. This shows the highly complex nature of an effective response to COVID-19 in the Rohingya refugee camps. After months of traditional measures and the development of undesirable side effects of these, vaccines can be a more long-term solution for an effective COVID-19 response in the Rohingya refugee camps, as different COVID-19 vaccines have reached their final stage of development and some are even distributed.

Vaccines offer a faster opportunity to slow down the spread of COVID-19 [Grauer et al., 2020], and the Government of Bangladesh has published a first draft of their Vaccination Program. At the time of writing, just over 2% of the Bangladesh population is vaccinated, and the Bangladesh Government can play a key role to protect Rohingyas by including them in their vaccination program [UNHCR, 2021a]. But at the same time, Bangladesh suffers from high vaccine scarcity and delivery problems, which is not expected to change in the upcoming months. In order to deal with vaccine scarcity, the government needs to decide on whom to prioritize for available vaccines. This is a complex task, as decision-making on vaccine allocation not only depends on vaccine availability, but also ethical factors should be weighed.

To support and improve the COVID-19 response in Rohingya camps, this research aims at comparing different COVID-19 vaccine allocation strategies which can be applied to the Rohingya population. Here, not only health-related risks are considered for an effective response, but also economic values which serve as a source of livelihood generation. To do so, a main research question is formulated which guides this research: ***What vaccine allocation strategies can be identified as an effective trade-off between allowing individual interactions and controlling COVID-19 infections in an open-system refugee camp settlement?***

In order to answer this question, a system is defined which is an integration of four concepts: (1) refugee-host interactions in an open-system refugee camp, (2) limited camp openness, (3) vaccine allocation and (4) COVID-19 transmissions. Through a literature review on these concepts and by conducting several interviews with experts on humanitarian assistance operations in the Rohingya refugee camps, these concepts were studied and translated into a model. This model describes an *open-system refugee camp*: on a daily basis, Rohingyas interact other Rohingyas and with host communities at shared facilities such as a bigger market, in-camp shops and other more informal meeting-points. These interactions serve as a source of income or livelihood-generation, but also risk the *transmissions of COVID-19*. Transmissions are reason for the Bangladesh Government to implement *limited camp openness*, which is referred to as the limiting of people's interactions in the open-system trough different types of lockdowns. As a more long-term solution for balancing livelihood-generating opportunities and controlling the number of COVID-19 infections, *vaccine allocation strategies* are analyzed: (1) the *Elderly first* and (2) *Children first* strategy prioritize elderly or children respectively. The (3) Equalizing strategy creates equal access to vaccines for everyone. The (4) *Bangladesh only* strategy is applied to explore the effect of excluding Rohingyas from the vaccination program. And the (5) *Transmission group* strategy, which prioritizes age-groups with a high risk of transmitting COVID-19.

These concepts and their dynamics are applied to a case study, which is one of the sub-blocks of the Nayapara RC Rohingya Refugee Camp in the Cox's Bazar region of Bangladesh. Through this case study, an Agent-based Modelling (ABM) model was constructed. With this model, it was aimed to explore, analyse, compare and interpret the effects of the five vaccine allocation strategies in combination with variations of different types of lockdowns, variations in limited capacity for in-camp facilities and different types of individual refugee behavior. With the outcomes following from this model, it is not aimed to propose a *single best solution*. Rather, the aim of this research is to gain insights on the dynamics between concepts and under what conditions an effective strategy can be formulated in context of a Rohingya refugee camp. This means, this research and its outcomes are exploratory by nature.

To generate insights from the model, experiments were set-up and simulated in various simulation runs. Experiments were performed in four categories: for testing (1) a base case model, (2) the effect of implementing limited camp openness (3) the effect of the five vaccine allocation strategies and (4) combined effects of both non-vaccine and vaccine related measures. The first category is used to get an better understanding of the model, where and how infections are most likely to occur and what role the influx of host communities plays here. The second and third categories are use measure the effectiveness for better controlling and reduce infections on one hand and to maximize interactive freedom between refugees and host communities on the other. With the last category, it is studied if limited camp openness and different vaccine allocation strategies can be more effective when both are combined.

These experiments lead to several insights which can be used by decision-makers in the COVID-19 Response of the Rohingya camps, which have lead to five general conclusions: Firstly, the influx of host communities of significant influence for triggering a COVID-19 outbreak in the refugee camp. From the moment a case is registered here and no measures are imposed, a large outbreak is a likely result. However, the host community does not significantly influence the speed and scale of the spread. A second insight explains the speedy spread infections in the open camp: an important cause of infections is found to be on locations with high concentrations of refugees and host communities. Over 80% of infections were measured at the vicinity market and the seven in-camp markets. Here, young adults are most significantly infected, as these are most active in the camp. An approximate 7.7% of all infections results in an severe/critical infection, which is highest for older adults and elderly. Thirdly, limited camp openness can best be imposed in a dynamic way, based on the assessment of weekly infections. From a perspective of controlling the epidemic spread, this can be as effective as an unconditional lockdown, but can still maintain a 60% of refugee-host interactions, compared to only 20% for an unconditional lockdown. A fourth conclusion relates to the effectiveness of vaccine allocation strategies. To control and reduce total infections in general, it is most effective to prioritize elderly (> 60 years) or transmission groups (young adults, 18-40 years). This is due to the fact that for these strategies a high share of highly susceptible (elderly) and highly transmitting (young adults) are vaccinated. Vaccinating children or creating equal access for vaccines is less effective, as the share of highly susceptible, non-vaccinated age-group remains too high. Lastly, excluding Rohingyas from the vaccination program is ineffective, as it still causes a large outbreak inside the camp. Furthermore, to reduce health-related risks, it is most effective to prioritize elderly. In this age-group, the largest share (60%) of severely and critically symptomatic infection is registered. To improve economic benefits expressed in maximizing refugee-host interactions, it is most effective to prioritize transmission groups (young and older adults). Especially when vaccinated refugees and host communities are always allowed at markets, the last strategy is really effective. However, this effectiveness is significantly lower if vaccinated individuals can still be infectious to others. Here, the prioritization of transmission groups is most sensitive, as the share of vaccinated age-groups with a high-risk transmission profile is high and the share of high-risk vulnerability people is also high.

This leads to the last and fifth conclusion, which is used as a basis for answering the main research question. Namely, an important insight from the analyses is the implicit trade-off between the Elderly first and Transmission group strategies, which are in general most effective to control COVID-19 infections (see figure 0.1). The benefits for prioritizing of transmission groups are mainly economic, as this strategy allows for 8% more refugee-host interactions. This is a significant difference, given the fact that any disruption of income or livelihood generation heavily impacts both refugees and host communities. However, the number of severe and critical cases for this strategy are more than three times higher for this strategy compared to the Elderly first strategy (EF strategy). It shows the complex nature and ethical task of deciding on an allocation strategy. Picking the "right" vaccine allocation strategy is not possible, as shown by this trade-off. This research does not aim to propose an answer for this weighing these ethically conflicting objectives between strategies. Rather, the trade-off is marked, quantified and can therefore be used for more effective decision-making when formulating an allocation strategy for COVID-19 vaccinations.

Also, these conclusions should not be interpreted in isolation. For the interpretation of the model outcomes, two general implications should be kept in mind. The first implication relates to the many assumptions which were made to create a feasible model. These assumptions were sometimes unavoidable, as information on certain concepts was in-

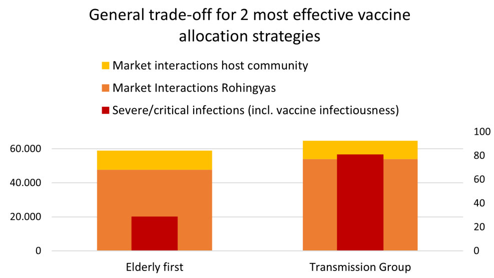


Figure 0.1: The main trade-off for an effective strategy for refugee-host interactions & severe/-critical infections

complete or not available. For example, academic literature on COVID-19 grows every day, but is still limited. Therefore, some assumptions were based on estimations, educated guesses by experts or derived from secondary sources. Also, assumptions were made to grasp the sub-concepts into a feasible model, for which conceptual mechanisms were simplified. This was needed, as scoping down to higher levels of detail would have significantly increased the computing power of the model. A second implication relates to the high level of context-dependency of the system of study. As many concepts were simplified, and not every contextual aspect of a Rohingya refugee camp could be captured into one model, one should keep in mind these contextual factors. This was highlighted by validating the model, which points out a high theoretical validity of the model outcomes when comparing these with other studies, but a lower validity when putting the outcomes in a real-world perspective. For example, Rohingyas were assumed to be fully willing to receive vaccines, which is highly dependent on contextual factors, such as trust and access to information on vaccine. As factors as such could were not all captured in the model, these implications should be kept in mind for real-world policy implementation.

But overall, the outcomes of this model are judged to be valuable for both real-world application and contribution to the academic world. For example, the outcomes can be used by decision-makers (such as the *Technical Advisory Committee on Immunization of Rohingyas*) on the roll-out of the COVID-19 vaccination program in the Rohingya camps. In the academic world, the outcomes can be used as additional insights on two branches of literature which relate to *effective refugee camp response operations* and to the *vaccine supply chain*. As this research combines both, an extra link is created between two branches of literature.

Lastly, some recommendations for further research were identified. This is mainly concentrated around extending the model on vaccination and transmission-specific characteristics. The model can be further extended by studying the effect of the need of multiple vaccines per individual, losing immunity over longer periods of time, over different levels of vaccine efficacy or by studying the effect of vaccine allocation strategies over more specific predefined sub-groups. Also, it is recommended to build forth on this research by further discovering scenario spaces. Due to a lack of time and highly computational model, experiments could not be run over a broad range of parameter ranges. With more insights on the solution spaces of this model, more robust conclusions can be drawn which would further improve decision-making on an effective COVID-19 response in Rohingya camps.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

WHO World Health Organization vii
UN United Nations 6
SDGs Sustainable Development Goals 5
ABMS Agent-Based Modelling Simulation 15
ABM Agent-based Modelling viii
UNHCR United Nations High Commissioner for Refugees 5
UML Unified Modeling Language 29
IVD WHO Immunization and Vaccine Development 12
NDVP National Deployment and Vaccination Plan for COVID-19 Vaccines 3
COVAX COVID-19 Vaccines Global Access 3
MOPH Ministry of Public Health 125
SAGE Strategic Advisory Group of Experts on Immunization 14
TLCs Temporary Learning Centres 30
KPI Key Performance Indicators 5
EF strategy Elderly first strategy ix
CF strategy Children first strategy 45
EQ strategy Equalizing strategy 45
BO strategy Bangladesh only strategy xvii
TG strategy Transmission group strategy 46

1 INTRODUCTION

1.1 PROBLEM INTRODUCTION

1.1.1 Background: The COVID-19 Outbreak

As for many of us, 2020 was a year overshadowed by the outbreak of COVID-19. COVID-19, an infectious virus which was first registered in December 2019, resulted in a global outbreak [Wu et al., 2020]. On March 11 2020, the WHO officially declared the spread of COVID-19 as a pandemic. At the time of writing, COVID-19 has cost almost two million lives in 191 different countries [John Hopkins University, 2021].

In an early stage, national authorities all around the world introduced different types measures, such as lockdowns, social-distancing rules, wearing mask regulations or compulsory stay-at-home isolation for sick people. In this way, social contacts were limited to reduce the risk of COVID-19 transmissions. In general, these measures proved to be highly effective for reducing the number of contagions [Hsiang et al., 2020] and protecting vulnerable people and healthcare systems [Fowler et al., 2020]. However, also new challenges have emerged regarding the social and economic impact of COVID-19 [of Sciences, 2020; Goolsbee and Syverson, 2021].

1.1.2 The Rohingya Refugee Camps in Bangladesh

These challenges are most significant in particular for poor, vulnerable people who live in refugee camps [Wright et al., 2020; Beech and Hubbard, 2020]. One highly vulnerable group are the Rohingya refugees [Beech and Hubbard, 2020]. The Rohingyas are a Muslim minority from Myanmar, of which many were forced to flee their home country as a result of being a target of political conflicts, violations and other human right disruptions of the Myanmar regime [UNHCR, 2020d]. Since 2017, around 1 million Rohingyas are hosted in refugee camps in Bangladesh, which is one of the largest and most densely populated refugee camps in the world [UNHCR, 2020d]. In these camps, Rohingyas live in overcrowded shelters, sometimes hosting up to seven people in a single shelter. With only half of the Rohingyas to have access to proper and clean drinking water, food, sanitation and healthcare facilities, the vulnerability of the Rohingya refugees is high and their dependence on external aid is significant [ACAPS, 2020; UNHCR, 2020e; Alam et al., 2019; UNHCR, 2021].

1.1.3 Rohingya Refugees & Host Communities Benefit from Interacting with Each Other

Despite their high vulnerability, one can also notice small progress has been booked in the last decades. Stimulated by different projects, initiated by humanitarian aid organizations and the Government of Bangladesh, more opportunities have been created for refugees to participate in livelihood-generating activities and to become more self-reliant [Buheji et al., 2020; UNHCR, 2020a,c]. A small fraction of the Rohinyas (approximately 50.000) is allowed to leave and enter the camp, and inside and along it borders different (informal) economic activities have emerged [Filipski et al., 2020].

An illustrative example of these improvements is the increased growth of cooperation between Rohingya refugees and host community people from Bangladesh. As a result of growing interactions between both populations, small economies have emerged. These (mostly informal) economic structures centre inside and around the refugee camp boundaries, where some sort of goods-production, exploitation of commercial networks or use of capital can be recognized. In the camps, trading centres and local markets exist, where both refugees and people from host communities buy and sell their goods [Werker, 2007; Rosenbach et al., 2018]. As a result, both Rohingya refugees and host communities have become less dependent on external aid as they reap the benefits from their economic cooperation, with an improvement of livelihoods as a result [Alloush et al., 2017; Hsan et al., 2019].

1.1.4 COVID-19 Threatens Livelihood-generating Refugee-Host Interactions

But since the outbreak of COVID-19, this livelihood-generating progress is under pressure. As from the moment when the first COVID-19 case was discovered in the Rohingya camps in May 2020, many of the aforementioned social measures were introduced by the Bangladesh Government, which impacted the cooperative developments. To limit interactions between Rohingyas and host communities as a source of potential COVID-19 transmission, a strict lockdown was imposed for the camp and fences were built around the camp boundaries IDC [2020]. The impact of this was far-reaching, as even the influx of essential workers and goods into the camps were limited in the initial months of the outbreak [Dempster et al., 2020]. And next to this strictly regulated camp lockdown, social measures were imposed inside the camp, such as cross-camp travel restrictions, shut-downs of local markets and refugees being forced to stay inside their shelters Godin [2020]; Vonen et al. [2020]; Dempster et al. [2020].

As a result of the limited possibilities for Rohingyas and host communities to interact, an increased growth of income insecurity is now determined in the camps. For example, an estimated 3 out of 4 refugees have lost a significant part of their incomes as result of contact-limiting lockdown-measures [Bukuluki et al., 2020]. This is problematic, as for the Rohingya refugees and host communities who are already vulnerable, a drop of income can reduce their ability to obtain essential resources such as food, water and healthcare [Kamal et al., 2020; Bukuluki et al., 2020].

1.1.5 The Complex Nature of Balancing Health and Economic Related Factors for Effective COVID-19 Response in Rohingya Camps

Whereas livelihood-generating activities are under pressure since COVID-19, controlling the spread of COVID-19 with contact-reducing measures is essential. As the Rohingya camps are overcrowded, the transmission of an infectious virus is easy [Shokri et al., 2020]. Two studies conclude, if no active contact-reducing measures are imposed, a single infection in the Rohingya camps will most likely cause a bigger outbreak [Hernandez-Suarez et al., 2020; Truelove et al., 2020]. And if the camps remain open, a high chance of spillovers of infection from the the camp to the local population is estimated [Gilman et al., 2020].

Although these measures in theory can be very effective for controlling the spread of an infectious disease [Grauer et al., 2020], questions are raised on whether it is feasible if and for how long these measures can hold in context of the Rohingya camps. Namely, the structural nature of refugee camps does not lend itself well for complying with contact-reducing measures, as they are overcrowded and facilities for proper sanitation usually lack [Truelove et al., 2020]. Also, these measures require a disciplined and structural change in behavior and living patterns of the refugees, which is practically impossible in the camps [Alemi et al., 2020].

As COVID-19 seems to even further increase the Rohingya's vulnerability, it is arguable how long basic measures for preventing the transmission of COVID-19 can hold. On one hand, high compliance to stick with the rules by a large share of a population is needed to control the spread of COVID-19 inside and out of the Rohingya camps [Wright et al., 2020; Lewnard and Lo, 2020]. On the other hand, these measures increase the economic vulnerability of refugees, affecting their willingness to comply with these measures Wright et al. [2020]; Dempster et al. [2020]. This is backed with growing research which concludes people living in poor conditions are less likely to comply to COVID-19 rules. In many cases, the economic consequences weigh of COVID-19 restricting measures weight higher than health-related consequences from individual's perspectives [Wright et al., 2020].

This sheds the light on the thin line between factors which balance the livelihoods of refugees like the Rohingyas. Taking away risks to prevent the spread of a potentially deadly virus causes news problems for people living on the edge of survival. Therefore, a more balanced solution for protecting both health and economic-related values is needed in case of the Rohingya refugees.

1.1.6 The Bangladesh Vaccination Program as a Potential Long-term Solution

As a long-term solution, many authorities point towards the opportunities of vaccines [Bartovic et al., 2021]. Vaccines offer a faster way to create group immunity and slow down the spread of COVID-19 [Grauer et al., 2020]. In January 2021, the WHO released the COVID-19 Vaccines Global Access (COVAX) initiative and corresponding National Deployment and Vaccination Plan for COVID-19 Vaccines (NDVP), which serve as a guidance for rolling out vaccine programmes in low- and middle income countries [World Health Organization, 2021; WHO, 2020a]. This advice was followed up by the Government of Bangladesh, which published the *"Operational Guidelines for COVID-19 Vaccination for Forcibly Displaced Myanmar Nationals"* (i.e. the Rohingyas) in May 2021. In this document, the initial Vaccination Program for COVID-19 vaccines was presented for Bangladesh, including the Rohingyas. By including the Rohingyas in the Bangladesh NDVP the Government aims to anticipate on the availability of vaccines delivered through the COVAX program.

However, at the time of writing this research, vaccines are yet to be delivered in Bangladesh. Guided by high levels of scarcity, an allocation problem exists on whom to prioritize for the first batches of vaccines. Many many countries, like Bangladesh, these prioritization strategies are focus on reducing the health-related consequences of COVID-19 [World Health Organization, 2021]. To do so, the Bangladesh Government has decided to prioritize elderly, as this age-group is most vulnerable.

But it can be argued whether this allocation prioritization strategy is effective in context of the Rohingyas. Namely, the Rohingya population is relatively young, with only 5% of its population above 60 year of age [Lopez-Pena et al., 2020] and relatively low numbers of deaths related to COVID-19 were registered. Potentially, an alternative prioritization might be more effective. For example, it could be more efficient to prioritize Rohingyas who have a higher risk of transmitting COVID-19 to others as are more interactive with others. Prioritizing these groups can be beneficial as well, as their interactions reflect their economic value which helps to sustains their families.

1.2 RESEARCH GAP & QUESTION

In this research, different vaccine allocation strategies are studied and analysed in context of an open-system refugee camp. An open-system refugee camp refers to interactions which take place between refugees and host communities outside the camp environment. Vaccine allocation refers the the decision on whom to prioritize for vaccines which availability is insufficient to cover a whole population. Both topics were studied with an extensive literature review (see chapter 2), which highlighted several important knowledge gaps. The overarching research gap which is identified and researched in this research are the *dynamics* between an open-system refugee camp with refugee-host interactions and COVID-19 infections following these interactions. Furthermore, it is studied if different types of camp openness in combination with vaccine allocation strategies can be balancing mechanism for controlling these infections. Up to the writers knowledge, no studies focus on these dynamics. However, several studies point towards the relevance of an academic view on these dynamics, for several reasons. A broad branch of literature has studied the increased importance of interactions between refugees and host communities, as these have improved livelihoods for both. For example, Werker [2007] presented a framework for such an open-system refugee camp and how governmental policies can improve its economic system as a result of opening its borders. The most up-to-date research found on the benefits of such an open-system was conducted by Filipski et al. [2020], who presented a qualitative improvement of incomes for refugees as a result of interactions with the host communities. However, none of these studies focus on the (temporarily) opening/closing of such a system and the impact this has on the economic refugee-host interactions. This is a first research gap addressed in this study: since the outbreak of COVID-19 , refugee camps were temporarily closed and interactions between refugees and host communities were cut-off. This research aims to focus on how to release the burden of these limited interactions, with vaccines as a long-term solution. As COVID-19 vaccines are scarce, special focus is set on how to allocate these vaccines effectively. This leads to the second research gap, which relates to studies on vaccine allocation. Duijzer et al. [2018] presents an overview of most recognized studies on vaccine allocation, but none of these studies focus on open-system refugee camps. Open-system refugee camps are unique, as demographic characteristics of a refugee population can be completely different from the host community. This creates different dynamics, as refugee camps can relatively easily be opened and closed physically. This research focuses on the influence of a (limited) influx of host communities on the potential cause of a COVID-19 outbreak in a refugee camp, which is not studied earlier. A third research gap which is found and guiding this research is the nonexistence of studies which focus on the application of vaccines as a measure for controlling COVID-19 outbreaks in a refugee camp. Different studies have been conducted on the implementation of non-pharmaceutical measures such as social distancing, wearing masks or quarantining and its effect on controlling infections (e.g.Truelove et al. [2020] or Hernandez-Suarez et al. [2020]). However, these studies also point towards the low effectiveness of these measures in real-life, as social distancing is hard in refugee camps. This research aims to focus on a combination of different types of camp openness regulation (for contact-reduction) and vaccines. Both are assumed to reduce the speed of an COVID-19 outbreak and reduce absolute infections and therefore make it possible to reopen the camp earlier. Here, an economic approach is chosen which is uncommon in the field of the vaccine supply chain Duijzer et al. [2018]. Namely, most studies focus on the minimizing of health-related risks from an infectious virus when comparing vaccine allocation strategies. In this research, a balance for minimizing risks for health and economic values is combined.

Based on the problem introduction from previous section and the identified knowledge gap presented above, the aim of this research is to give an answer to the following research question: *What vaccine allocation strategies can be identified as an effective trade-off between allowing individual interactions and controlling COVID-19 infections in an open-system refugee camp settlement?*

1.3 RESEARCH OBJECTIVES

With this research question, a slightly different approach is chosen for comparing different strategies on the allocation of COVID-19 vaccines. Namely, a high share of literature on effective vaccine allocation focuses on minimizing health-related risks (such as mortality and morbidity rates and pressure on hospitalization and healthcare facilities). In this research, it is explored whether it can be effective to value economic factors more equally to health-related factors when deciding on whom to prioritize for the available vaccines. By comparing different vaccine allocation strategies in context of a refugee camp, it is determined whether vaccine allocation strategies can be effective for finding a trade-off between the allowing of interactive freedom (representing economic value) whilst reducing COVID-19 infection (representing health-based value).

For finding this trade-off, the dynamics between four different concepts are studied. These concepts are:

- **Sub-concept 1:** Interactions in an open-system refugee camp
- **Sub-concept 2:** Restricting COVID-19 measures
- **Sub-concept 3:** COVID-19 vaccine allocation strategies
- **Sub-concept 4:** A COVID-19 transmission model

An *open system refugee camp* refers to the aforementioned possibility of *interactions* between refugees and host communities, as a source of income or livelihood-generation. As a result of interactions, *COVID-19 transmissions* can be a result. Transmissions are reason for the Government to implement *restricting COVID-19 measures*, which is referred to as the limiting of people's interactions in the open-system. As a more long-term solution for balancing livelihood-generating opportunities and controlling the number of COVID-19 infections, *vaccine allocation strategies* are analyzed. To measure the effect of both measures and vaccine allocation strategies, a *COVID-19 transmission model* is used to measure the spread of COVID-19 and if this allows for more interactions in the open system. These sub-concepts are further explicated and defined in chapter 2).

To study the dynamics between these sub-concepts and to find a trade-off for balancing economic and health-related values, two main Key Performance Indicators (KPI)s are chosen to measure the effect of different dynamics:

- **KPI 1:** Refugee-host interactions
- **KPI 2:** COVID-19 infections

Refugee-host interactions refer to the interactions between refugees and host communities, and are chosen a factor which represents livelihood-generation for both populations. Therefore, this KPI reflects the economic-based value. COVID-19 infections refer are a potential result of these interactions, and reflect the health-based value in this research. In chapter 4, these KPIs are further discussed.

1.4 SOCIETAL RELEVANCE OF THIS RESEARCH

This research is societal relevant for different reasons. As the negative impact of COVID-19 on refugee camps seems inevitable, the key focus is how to make up for the losses. These losses can be expressed in many ways, which in this research is expressed to be the limited economic freedom of Rohingya refugees and host communities. In this way, this research build forth on a global strategy on improving *Refugee Livelihoods and Economic Inclusion* was set-up by the United Nations High Commissioner for Refugees (UNHCR). COVID-19 sets extra pressure on this goal, as it is expected to have a big impact on refugee's economic vulnerability. Therefore, research is needed which supports effective COVID-19 responses with more economic focus. As this research seeks for solution to balance economic freedom to interact with reducing COVID-19 infections, this research can contribute to a more effective response through both economic and health-related values.

A second societal contribution relates to the practical implementation of the WHO COVAX program, which aims to create *"global equitable access to COVID-19 vaccines"* [WHO, 2020a]. As different COVID-19 vaccine allocation strategies are researched in context of refugee camps, an implicit goal of this research is to include refugees in vaccination programs. Creating equitable access to vaccines is important, as it is in line with everyone's right to healthcare regardless any religious, racial, cultural matter, according to the Human Rights Watch [HRW, 2021].

The importance of this study is also reflected by how it can contribute to achieving the Sustainable Development Goals (SDGs). The SDGs, which need to be achieved in 2030 [United Nations, 2016], play a central role for decision-makers setting-up national policies and development strategies [Moyer and Hedden, 2020]. According to Moyer and Hedden [2020], COVID-19 will have a major impact on achieving the first four SDGs for vulnerable minorities in developing countries, which are respectively (1) No Poverty, (2) Zero Hunger, (3) Good Health and Well-being & (4) Quality of Education. On top of that, at least 12 of the 17 SDGs will be negatively influenced by the (in)direct impact of COVID-19, according to the United Nations (UN).

1.5 SCIENTIFIC CONTRIBUTION OF THIS RESEARCH

Next to the societal relevance of this study, this research also represents scientific value. As mention in the research gap, no studies can be found which study different COVID-19 vaccine allocation strategies in context of refugee camps. Therefore, this research adds value to two branches of literature, relating to literature on *logistics in the vaccine supply chain* and literature on effective *COVID-19 responses in refugee camps*.

The vaccine supply chain has been studied extensively, as stated and reviewed by Duijzer et al. [2018]. Vaccine allocation is one of its core elements, and should be judged a very important element in decision-making, especially when vaccines are scarce [Duijzer et al., 2018]. On top of that, vaccine allocation is judged the only 'unique' element of the vaccine supply chain when comparing with other supply chains [Duijzer et al., 2018; Dasaklis et al., 2012]. Therefore, the need for up-to-date and context specific insights on this vaccine allocation process is an important insight for supported decision-making.

Secondly, this research adds value to scientific research on COVID-19 responses in refugee camps, related to the dynamics between the four concepts which were introduced. As will be introduced in chapter 2, various literature studies exist which highlight one or two of these concepts. However, up to the writers knowledge, no literature exists on the balancing effect of vaccine allocation strategies, COVID-19 transmissions, and movement-restricting measures in an open-system refugee camp environment. By studying the dynamics between these concepts, a new light is shed on the branch of literature which supports decision-making in refugee camp environments in combinations with infectious diseases and epidemics.

1.6 OUTLINE RESEARCH

This research is structured by ten chapters. In chapter 2, a literature review is presented on relating topics which were introduced earlier this chapter. From this, a research gap is identified and defined, which serves as an academic basis to conduct this research. As a first step to demarcate the boundaries of this research, chapter 3 presents a research design. Chapter 4 then presents a conceptualization and formalization of different sub-concepts as derived from the literature review, and integrated into one system which is used for study. These concepts are translated to a model for analysis, presented in 5. In chapter 6, the experiments which have been carried in this research are introduced. The outcomes of these experiments are presented in chapter 7. In chapter 8, model outcomes are validated and interpreted. In chapter 9, outcomes are discussed and reflected upon. Lastly, chapter 10 draws conclusions, related to the sub-questions and main research question for this research.

2 LITERATURE REVIEW

Chapter 2 presents a literature review on four sub-concepts, to give an answer of the first and second sub-questions of this research: **Sub-question 1:** What drives interactions in an open-system refugee camp settlement, influenced by restricting COVID-19 measures? **Sub-question 2:** How can different vaccine allocation strategies be defined in context of a refugee camp settlement? This literature review is structured trough three main sections in which the introduced sub-concepts are discussed. As a starting point, a search plan in presented in section 2.1. In section 2.2, literature on sub-concept 1 (an open-system refugee camp) and sub-concept 2 (on restricting COVID-19 measures) is reviewed. In section 2.3, a literature review is presented on sub-concept 3 (vaccine allocation) and on sub-concept 4 (transmission models). In 2.4, the literature is synthesized and explained how it is used in this research. Lastly, section 2.5 concludes.

2.1 SEARCH PLAN

To study the above mentioned subjects, the following search plan has been conducted. For the refugee camp interactions, the keywords 'refugee camp', 'host community' and 'interaction' were used initially, to study several academic papers from Google Scholar and Scopus. Here, a main assumption was refugees interact with host communities on economic and social grounds. With new insights from this general search on interactions in refugee camps, a more specific search was done on social, economic and cultural interactions between refugees and host communities. For this, the keywords 'economic interaction', 'social interaction' and 'cultural interaction' were studied more specifically in combination with 'refugee camp' and 'host community'. For the impact of COVID-19 and other epidemics on these interactions, academic papers published from 2020 were studied, using the key words 'COVID-19', 'epidemic', 'refugee camp', 'lockdown' and 'movement'. Additional insights were gained through snowball sampling. For vaccine allocation strategies, the keywords 'vaccine allocation', 'strategy', 'COVID-19' and 'epidemic' were used. From this search, 26 academic papers were selected and studied, of which 9 covered the COVID-19 epidemic. An overview of these papers is presented later in this chapter, and can be found in table 2.1.

2.2 INTERACTIONS & COVID-19 MEASURES IN OPEN-SYSTEM REFUGEE CAMPS (CONCEPT 1 & 2)

This section discusses literature which is used to answer sub-question 1 in this research. To do so, literature is studied on relating concepts to this question: section 2.2.1 explains literature on refugee-host interaction in an open-system refugee camp. Section 2.2.2 explains how COVID-19 measures have influenced these interactions and how this affects individual behavior of refugees. Later in this chapter, the insights from this review are translated to how these are used in context of the Rohingya camps.

2.2.1 Refugee-Host Interactions in Refugee Camps

Definition & theory

In different refugee camp contexts, various interactions between refugees and people from the host community can be recognized. UNHCR describes refugee-host interactions as the social & economic interactions which take place between refugees and host communities, both inside and outside refugee camps [UNHCR, 2011], and are considered an important factor in the integration of refugees with local communities in long-term refugee camps. Refugee-host interactions happen when refugees, people from host communities, goods and capital leave and enter the camps [Alloush et al., 2017], and is a result of both population's attempts to fulfill the potential opportunities of increasing their welfare and livelihoods [Agblorti, 2006; Whitaker, 1999; Zakaria and Shanmugaratnam, 2003]. Successful integration of refugees with host communities depends un several factors, such as whether refugees live inside the camps or in host communities themselves, the negative or positive economic impact refugees have on the host communities and ethnic differences [Bakewell, 2002; Porter et al., 2008].

Azad and Jasmin [2013] explain refugee-host interactions as a process which takes place on three different levels: legal, social and cultural & economic interactions. Legal interaction occurs when refugees are granted legal rights to move freely, for example by receiving official refugee status. Social interaction is the participation of refugees in the social life of host communities [Azad and Jasmin, 2013]. Economic interactions happen when refugees participate in local economies in hosting country. These interactions benefit the refugees, as they can become more self-reliant, less dependent on humanitarian aid and they contribute to improve local economies [Azad and Jasmin, 2013; Cavaglieri, 2008].

The focus of this research lies on economic interactions, leaving legal and social interactions aside. Namely, economic interactions are best to describe the interactions between the Rohingyas and host communities in Bangladesh. Studies by Filipski et al. [2020] and Rosenbach et al. [2018] conclude economic interactions between Rohingyas and the host community are significantly predominant over social interactions. This is in line with studies concluding no social integrating progress has been booked for years between Rohingyas and Bangladeshi (e.g. see Jerin et al. [2019], Ullah [2011]). Legal interactions do exist in Rohingya refugee camps, but these can be expressed as economic interactions: around 50.000 refugees have a legal refugee status, which gives these Rohingyas permission to leave the camp and seek for employment. According to a recent survey by Filipski et al. [2020], these legal refugees use their status only for things which can be translated directly to economic transactions: refugees with legal status mainly go out of the camp boundaries to work.

For economic interactions, it is further specified by whom, where and how these take place. An broad range of literature focuses on *why* refugee-host interactions exist, which is not in scope of this study. Namely, the focus is set on *how* interactions in refugee camps can lead to COVID-19 infections (the link between interactions and COVID-19 is discussed more briefly in section 2.2.2).

Rohingya Camp Economies Drive Economic Refugee-Host Interactions

To understand how economic refugee-host interactions happen in a refugee camp, the economic activities must be understood as a basis. Namely, economic interactions are a result of economic activities which emerge inside and around refugee camps [Werker, 2007; Alloush et al., 2017; Betts et al., 2014]. Literature refers to this as *refugee camp economies* (e.g. Werker [2007], Betts et al. [2014]) or the *economic life* (e.g. Alloush et al. [2017]) inside and around refugee camps.

Refugee camp economic have created strong economic dependencies between refugees and host communities, addressed by studies on different refugee camp economies [Alloush et al., 2017]. These studies conclude both refugees and host communities reap the benefits from their interactions as in many cases the economic conditions have improved [Taylor et al., 2016]. For example, Omata and Kaplan [2013] studied refugee-host interactions on local markets in Uganda, recognizing extensive engagement patterns between host- communities and refugees. The study concludes refugees participate in local economies extensively, which is a result of social networks bringing them together. Betts et al. [2019] studied the same phenomenon in Kenya, concluding interaction between host communities and refugees exist between retailers and consumers. Here, refugees actively consume from local Kenyans, boosting consumption in general. Alloush et al. [2017] concludes refugee's inclusion in local markets raised consumption for both refugees and local people by 25%. Studies by Filipski et al. [2020] and Rosenbach et al. [2018] studied interactions between Rohingya refugees and the local Bangladesh communities, concluding extensive interactions between these groups over a wide range of economic activities.

Economic interactions are a result of four driving factors as named by Filipski et al. [2020]:

1. Type of economic activities
2. Location of economic activities
3. Ratio of refugees-host communities
4. Type of interaction

Types: Various types of economic activities can be recognized inside and around refugee camp settlement. Refugees and host communities work together, by trading, selling or buying each others products, offering their (labouring) services and setting-up small business enterprises. For example, types of economic activities recognized in and around the Rohingya camp settlements are retail trading, offering food or transport services and agricultural laboring.

Locations & ratio refugee-host community: The economic activities are executed by refugees and host communities through (informal) economic networks, which concentrate on (small) markets or in trading centres and with different compositions of involved actors [Werker, 2007; Betts et al., 2014; Alloush et al., 2017]. In general, economic activities exist on three types of places: inside the camps, on camp boundaries and in local communities [Taylor et al., 2016]. Inside camp settlements, trading centres and camp markets are the usual place where refugees meet each other and the local people to trade, buy and sell goods [Werker, 2007; Interview 1, 2021]. Here, main actors who participate in these markets are the refugees themselves, and a smaller number of local people if they are allowed to enter the camp site [Werker, 2007]. On camp boundaries, vicinity markets exist. These are market zones which are located on camp borders, where local roads meet the camp areas. In vicinity markets, the ratio of refugees and local communities participating on the market is usually much more mixed [Filipski et al., 2020; Rosenbach et al., 2018]). Outside the camps, refugees also participate in economic structures. The refugees, if they are not restricted by legal or physical boundaries, participate in local markets or work in shops, agricultural labouring or offer other services, together with host communities. The host community is usually more predominant here [Werker, 2007; Alloush et al., 2017].

Types of interactions: As a result of the above mentioned types of economic activities on different locations with different refugee-host rations, four types of interactions follow: customer interactions (customers buying goods in a shop), market interactions (markets selling food and other goods), credit market interactions (exchange of credits between buyers and sellers) and labouring interactions (working in a shop as an employee) [Filipski et al., 2020; Rosenbach et al., 2018].

2.2.2 Restricting COVID-19 Measures for Camp Openness

After the start of the spread of COVID-19, daily lives of people all around the world changed WHO [2020b]. A main factor reducing the number of interactions between people globally, were the contact-reducing measures introduced by governments all around the globe [Grauer et al., 2020]. In the Rohingya refugee camps, lockdown measures and restricting movements were introduced [IDC, 2020]. These measures lead to complete isolation of the camps, with severe socioeconomic consequences [Grauer et al., 2020; Anwar et al., 2020; Buheji et al., 2020]. These measures are discussed here, with a stressed importance on the perspective of refugees who need to comply with these measures. Namely, compliance is an important factor on the effectiveness of these measures [Grauer et al., 2020].

Lockdown Measures & Movement Restrictions

Different studies have been carried out on the impact of socially excluding measures, which are effective in case of an epidemic [Pellecchia et al., 2015]. Two effective social measures for COVID-19 transmission prevention are lockdowns and restrictions in movements. These measures are effective for controlling a virus, but have a severe economic consequence [Grauer et al., 2020]. In relation to lockdowns and restrictions in movements, different studies point towards the socioeconomic problems which occur for individuals, as a result of social and economic isolation. Firstly, social isolation triggers psychological problems, such as anxiety, stress and violence [Pellecchia et al., 2015; Jeong et al., 2016]. Fear for the disease at issue has an enforcing effect on psychological problems [Brooks et al., 2020]. Secondly, economic isolation leads to losses of income security and accessibility of essential goods and services [Singh and Singh, 2020]. This socioeconomic impact has also been studied in research on COVID-19 in refugee camps. As a result of camp settlement lockdowns and movement restrictions between different refugee camp blocks [Anwar et al., 2020], socioeconomic problems have grown. For example, in many refugee camps COVID-19 lead to an increased dependency on basic needs, such as water, food and healthcare [Kamal et al., 2020].

In Bangladesh, the Rohingya population suffers from exclusion and relatively high isolation. This was exacerbated by the camp lockdown and movement restrictions between camp blocks following from COVID-19, imposed by the Government of Bangladesh in March 2020. The camp sites are already relatively isolated, which grew in the months after COVID-19: in March 2020, the Rohingyas were prohibited to leave the camp sites [Sakamoto et al., 2020]. But after cases started rising, their freedom of mobility was further decreased: authorities started building fences around the camp to prevent refugees from going out in May 2020 [Islam and Yunus, 2020; IDC, 2020]. Consequently, socioeconomic conditions decreased.

Socially worsened conditions are mainly reflected by an increased sense of fear for COVID-19, an increased sense of uncertainty regarding the future and the increased violence inside the camp settlements, as concluded by El-Khatib et al. [2020]. Economically, conditions are problematic due to an increase of economic exclusion for the Rohingyas. For example, Rohingya's incomes dropped by 80% and more than 60% of the Rohingyas became inactive for income-generating activities since COVID-19 started [Sakamoto et al., 2020; Bodrud-Doza et al., 2020]. Also, as local in-camp markets for trading fresh food and other essential products were forced to close, dependency on external aid grew [Snowdon, 2020]: essential goods (such as agricultural inputs, water and food) could not enter the camp sites anymore [Islam and Yunus, 2020]. Shammi et al. [2020] concludes most important factors which indicate the socioeconomic impact for Rohingyas in Bangladesh: the perceived risk of community transmission, accessibility of essential services, the coordinative power of the government and their transparency and the availability of financial aid relief for the low-income population. A needs assessment on the Rohingyas in Bangladesh by UNHCR concludes the accessibility and availability of primary needs inside refugee camps has decreased: COVID-19 lead to an increased need for food & water, financial resources, shelters and income-generating activities [UNHCR, 2020b]. This assessment is supported by research of Kluge et al. [2020], concluding big shortages and lack of quality of food and water supplies.

Compliance to COVID-19 Measures in Refugee Camps

Lockdown measures and movement restrictions imply a top-down structure for the COVID-19 response in refugee camps. However, an important factor relating to the impact of COVID-19 in refugee camps is their autonomy and individual behavior [Bodrud-Doza et al., 2020]. Considering individual behavior of refugees is desirable for two main reasons: firstly, emergency responses in refugee camps have shifted to a bottom-up approach in the last decades. Response coordinators do so, by including refugees and making them an important part of the decision-making process [Easton-Calabria, 2015]. Secondly, as top-down responses in refugee camps usually work less effective in practice. Namely, a big number of refugees inside refugee camps have no legal refugee status and participate in informal structures [Filipski et al., 2020].

In case of an infectious virus, the effectiveness of the response highly relies on individual behavior related to compliance to measures. Only when measures are complied to by a large number of people, an infectious virus can be controlled [Hsiang et al., 2020; Anderson et al., 2020]. However, compliance to COVID-19 measures is economically costly and requires a structural behavioral change by individuals [Goolsbee and Syverson, 2021]. Especially for individuals in refugee camps, where socioeconomic conditions got worse, this is problematic, as living conditions are not in favor of contact reducing measures [Truelove et al., 2020].

Different studies have been carried out studying what factors influence individuals willingness to comply to the measures which were introduced by COVID-19. Chan et al. [2020] conclude individuals with higher confidence in healthcare systems show higher compliance to COVID-19 measures. Barrios et al. [2021] conclude the availability of social capital increases voluntary compliance. Brodeur et al. [2020] finds social trust is an important factor for reducing movements of individuals. Wright et al. [2020] finds a positive correlation between incomes and compliance to staying-at-home measures.

In refugee camps during the COVID-19 outbreak, all these factors studied in literature are not in favor of compliance to COVID-19 measures: in many refugee camps, healthcare systems lack proper facilities and capacity [Truelove et al., 2020]. Also, social capital is barely available in refugee camps and the dependency on external cash provisions is high [Dempster et al., 2020]. Social trust is also very low: Buheji et al. [2020] observe how refugees face increased social fear and higher income uncertainty. Kamal et al. [2020] observes higher levels of criminality & violence, economic stress and mental health problems, as a result of lower incomes and shortages of essential resources Kamal et al. [2020]. And as discussed in previous section, refugees face severe income-generating problems.

2.3 VACCINE ALLOCATION & TRANSMISSION MODELS (CONCEPT 3 & 4)

This section discusses literature which is used to answer sub-question 2 in this research. To answer this question, vaccine allocation is studied first with literature on reactive vaccine allocation (section 2.3.1) and decision-making for high vaccine scarcity (section 2.3.2). These sections serve as a starting point for a literature review on vaccine allocation strategies and different approaches, as presented in section 2.3.3. This academic overview is supplemented with practical insights from countries including refugees in the vaccine programmes. To analyse different vaccine allocation strategies, an overview of models is presented in section 2.3.4.

2.3.1 Reactive Vaccine Allocation

In refugee camps, refugees interact with each other and with the host communities [Azad and Jasmin, 2013]. However, these interactions were limited by lockdowns and movement restrictions, with severe socioeconomic consequences [Buheji et al., 2020]. To relief the burdens for individuals, experts point towards COVID-19 vaccines as a long-term solution [Helbing et al., 2010]. Here, an important role for response coordinators is to develop effective vaccine allocation programs. Effective vaccination programs reduce chances of local outbreaks of COVID-19 inside and outside refugee camps [Talukder, 2021; Gaynor, 2021]. Also, more interactive freedom for both refugees and host communities can be allowed [Mukumbang, 2020; UNHCR, 2020c].

National governments, supported by the WHO Immunization and Vaccine Development (IVD) and humanitarian organizations, are working on their NDVP. The NDVP is a supporting document for low & middle income countries, guiding the preparedness for allocating doses of COVID-19 vaccines when they become available [World Health Organization, 2021]. To operationalize vaccine allocation for this study, it is defined first. Duijzer et al. [2018] defines vaccine allocation as the process of deciding whom to vaccinate first. Here, response coordinators need to focus on the prioritization of specific sub-groups for receiving a vaccine, which is a common problem when vaccines are not available for a whole population [Tuite et al., 2010]. For example, one can prioritize vulnerable, high-risk sub-groups who face highest risks for their health. Or one can prioritize high transmitting sub-groups, covering the people contributing most to the spread of a virus [Duijzer et al., 2018].

Vaccination allocation programs can be categorized as either reactive preventive vaccinations: reactive vaccinations takes place in case insufficient vaccines are available. This happens in case of an unexpected, sudden outbreak of an infectious virus or disease, such as Influenza or COVID-19 [Duijzer et al., 2018; Duan et al., 2020]. Reactive vaccinations are the opposite of preventive vaccinations, which are distributed to people before an infectious disease occurs, such as malaria or tuberculosis [Duijzer et al., 2018].

2.3.2 Vaccine Allocation Decision-Making with Scarce Resources

Before distributing vaccines, vaccine allocation is an important task for decision-makers, such as governments and public health organizations. As vaccines are usually scarce in developing countries [Kochhar et al., 2013], these countries are faced with allocation problems in the emergency response. Here, decision-makers focus on analyzing what people should be prioritized and how this can change over time, which is a complex and ethical task [Duijzer et al., 2018]. This complexity is reflected by an ethical trade-off between effectiveness and equal allocation, which can be conflicting objectives: unequal allocation of vaccines (e.g. only prioritizing elderly) can be really effective (e.g. causing decreasing death-rates) [Keeling and Shattock, 2012]. Another complicating factor where conflicting objectives occur is when vaccines are allocated by multiple decision-makers with overlapping decision-making authority [Duijzer et al., 2018]. An example of this which is frequently recognized on context of scarce vaccine availability is global actors calling for re-allocation of vaccines, to anticipate on an emergency in another country [Mamani et al., 2013]. Other complicating factors for vaccine allocation with scarce resources, especially in developing countries are its large logistical challenges [Barbera et al., 2001; Aaby et al., 2006], the high levels and broad ranges of particularities of vulnerable people and the multidisciplinary nature for epidemic control [Dasaklis et al., 2012].

As around 85% of refugees worldwide live in developing countries, which are struggling to access sufficient COVID-19 vaccines, scarcity of vaccines is a prevalent issue in refugee camps [Talukder, 2021; Sharma et al., 2020]. Therefore, this research sets focus on scarcity of vaccines, to anticipate on the complex issues related to vaccine allocation problems in a refugee context. To do so, scarce supply of COVID-19 vaccines is considered an important input factor for different vaccine allocation strategies.

2.3.3 Vaccine Allocation Strategy Approaches

Previous section concluded vaccine allocation is driven by vaccine scarcity, which is the case for COVID-19. In literature, different studies on both COVID-19 and previous unexpected epidemics have been carried out using different approaches on vaccine allocation problems with scarce vaccines. An overview of these studies and approaches is presented in table 2.1.

These approaches not only depend on vaccine availability, but also on the process of assessing whom to prioritize for these vaccines, with what goal and in which context

Table 2.1: Literature review on scarce vaccine allocation in unexpected epidemics

Approach	Focus Approach	Study	Epidemic	Scarce Vaccines?	Use of SEIR[1] Model?
Geographic	Regions-based	Matrajt et al. [2013]	Influenza	x	x
		Keeling and Shattock [2012]	-		x
		Araz et al. [2012]	Influenza	x	x
		Wu et al. [2007]	Influenza	x	x
		Grauer et al. [2020]	COVID-19	x	x
		Thul and Powell [2021]	COVID-19	x	x
	Community/household-based	Tanner et al. [2008]	Various		x
		Ball and Lyne [2006]	-		x
		Ball et al. [2004]	-		x
		Ball and Lyne [2002]	-		x
		Becker and Starczak [1997]	-		x
Demographic	Age-based	Dalgıç et al. [2017]	Influenza	x	x
		Goldstein et al. [2012]	Influenza	x	x
		Mylius et al. [2008]	Influenza	x	x
		Wallinga et al. [2010]	Influenza	x	x
		Patel et al. [2005]	Influenza	x	
		Hogan et al. [2020]	COVID-19	x	x
		Matrajt et al. [2020]	COVID-19	x	x
		Farrell et al. [2020]	COVID-19	x	
		Buckner et al. [2020]	COVID-19	x	x
		Bubar et al. [2021]	COVID-19	x	x
		Chapman et al. [2021]	COVID-19	x	x
	Transmission-based	Lam et al. [2015]	Various	x	x
		Matrajt and Longini Jr [2010]	Influenza	x	x
		Dushoff et al. [2007]	Influenza	x	x
		Foy et al. [2021]	COVID-19	x	x
		Hogan et al. [2020]	COVID-19	x	x
		Thul and Powell [2021]	COVID-19		

[Duijzer et al., 2018; Dasaklis et al., 2012]. Two general vaccine allocation strategy approaches exist:

1. A geography-based allocation strategy approach

2. A demography-based allocation strategy approach

Geography-based Vaccine Allocation Approach

A geography-based allocation strategy focuses on allocating vaccines over different geographical regions [Duijzer et al., 2018]. Here, different studies have been carried out in two main streams. Firstly, vaccine allocation over different regions. These studies conclude the prioritizing of certain regions over other regions can have positive effects on the spread of an epidemic, especially for smaller populations and high vaccination coverage as concluded by Grauer et al. [2020] on COVID-19 and Araz et al. [2012] on Influenza. Thul and Powell [2021] conclude region-based vaccination allocation is effective, but only when the number of current infections can be validated accurately. Secondly, vaccine allocation over households and/or communities. These studies conclude a so-called *equalizing strategy* works effective, a strategy which *"leaves equal numbers of susceptible individuals in each household"* [Keeling and Ross, 2015, p.7]. Up the the writers knowledge, no research has yet been published on the household or community-oriented approach in context of COVID-19.

Demography-based Vaccine Allocation Approach

A demography-based strategy focuses on allocation of vaccines over demographic characteristics of people. Different from geography-based strategies, this strategy allows for studying interactions between subgroups and rank their vulnerability or contribution to transmissions [Duijzer et al., 2018]. Different studies have been carried out on this approach (see table 2.1), focusing on: vaccine allocation over age-groups, concluding the prioritization of young people (children) is most effective in early stages of an epidemic as children contribute most to transmission; vaccine allocation over high-risk vs. high transmission sub-groups, concluding high-transmission groups (such as children and young people) should be given priority as well in early stages of an epidemic. In epidemics with a high level prevalence (i.e. prevalence is referred to as the number of current cases in a population in a given time period), priority should be given to high-risk sub-groups [Wallinga et al., 2010]. An important difference with the geographical approach is the type of interactions between subgroups. When considering a geography-based allocation strategy, virus transmissions between different sub-groups is a lower risk than for a demography-based allocation strategy [Duijzer et al., 2018].

This approach is popular for studies on COVID-19. Matrajt et al. [2020] studied age-based vaccine strategies based on vaccine effectiveness, concluding high-risk sub-groups should be prioritized with ineffective vaccines. In contrast, young people should be prioritized for effective vaccines, as they contribute most to transmissions. Foy et al. [2021] studied vaccine allocation strategies on mortality and morbidity rates in India, through an age-based (i.e. demography-based) model. The paper concludes prioritizing the elderly reduced deaths the most. Factor related to vaccines increasing effectiveness of different strategies are the effectiveness of vaccines, the target coverage and speed of distributing vaccines. Non-pharmaceutical measures (e.g. wearing face masks and social-distancing) also had a positive effect. Thul and Powell [2021] focused on transmission sub-groups in highly dense areas, concluding decision-making was most efficient for containing the spread of COVID-19. Hogan et al. [2020] studied both, concluding the effectiveness of age and transmission-based approaches depend on availability of vaccines: with limited doses (covering up to 20% of a population), an age-based prioritization of high-risk sub-groups is most optimal, but targeting transmission sub-groups is more effective for larger vaccine supplies. Buckner et al. [2020] studied different age-based strategies for minimal deaths, losses of life years and infections. The study concludes the prioritization of the elderly and healthcare workers works most effective for these three different policy objectives. Bubar et al. [2021] studied two age-based strategies, concluding prioritization of people between 20-50 years is most effective for minimizing COVID-19 incidences and prioritizing people above 60 years old minimized mortality and death-rates. Chapman et al. [2021] studied demography-based strategies on prioritizing elderly and essential workers, concluding this is most effective for minimizing deaths and disability-adjusted life years. A more general conclusion is the prioritization through an age-based approach is most effective compared to other demographic approaches.

Choosing an Approach: Current Practices of COVID-19 Vaccine Allocation

From the studies, it can be concluded both approaches have positive results for controlling the spread of an unexpected epidemic. To chose an approach for COVID-19, the context of a vaccine allocation problem study is highly important [Privett and Gonsalvez, 2014]. This context, other than the dichotomy between demographic and geographic characteristics, depends on factors like as vaccine availability, the speed of delivery, characteristics of a type of vaccine and the current state of an epidemic (like its socioeconomic impact or current level of immunity) [World Health Organization et al., 2020]. From the literature review (see section **??**, it can be concluded a demography-based approach is most popular for studies on COVID-19 vaccine allocation studies. However, none of these studies have been carried out in context of refugee camps. Therefore, elements from both approaches have been used from other studies in this research. Some insights can also be gained from current practices of COVID-19 vaccine allocation programs, by studying different frameworks and NDVP's of countries including refugees in their vaccination program. At the time of writing, Jordan (700.000 refugees), Lebanon (2.1 million refugees & migrant workers) and Bangladesh (1 million refugees) have committed to include refugees, by making use of the Strategic Advisory Group of Experts on Immunization (SAGE) Values Framework. Up to the writers knowledge, the Government of Lebanon and Bangladesh have publicly included refugees in their official vaccination prioritization plans: the Lebanon NDVP NCC [2021] and the *Operational Guidelines for COVID-19 Vaccination for Forcibly Displaced Myanmar Nationals*, as a part of the Bangladesh NDVP [Government of Bangladesh et al., 2021].

Current Practice in Lebanon

In the Lebanon NDVP, lead by the Lebanon Ministry of Public Health and UN agencies, the aim is to reach a high level of immunity (i.e. 60-85% of the total population vaccinated). Here, the aim is to prioritize people *in an inclusive and non-discriminatory* *manner* [NCC, 2021], by including both citizens from Lebanon and non-citizens, such as refugees. When reviewing their vaccination allocation strategy, a combination of an age-based and transmission-based prioritization approach can be recognized: in initial stages, healthcare workers are given priority. In later phases, elderly (> 65 years), older adults with comorbidities (55-64 years), older adults (55-64 years), young people with comorbidities (16-54 years). With this approach, the Government of Lebanon prioritizes health-related objectives (minimizing mortality and morbidity-rates). In later phases, prioritization will be focused on socioeconomic-related objectives. A full prioritization schedule can be found in appendix C.2 [NCC, 2021].

Current Practice in Bangladesh

In the Bangladesh NDVP, lead by the Bangladesh Ministry of Health and Family Welfare, the aim is to vaccinate at least 80% of the Rohingya population. When reviewing their vaccination allocation strategy, an age-based prioritization approach is applied on both Bangladeshi and the Rohingya refugees, over different phases: Phase 1 covers stage A & B: stage A covers healthcare workers (> 18 years) and elderly (> 40 years). Stage B covers adults (18-39 years). In phase 2, young people (< 18 years) are prioritized. Phase 3 considers pregnant women. A full prioritization schedule can be found in appendix C.3 [Government of Bangladesh et al., 2021].

2.3.4 Transmission Models for Analysing Vaccine Allocation Strategies

Simulation Models for Studying Vaccine Allocation Strategies

To measure the effectiveness of different vaccine allocation strategy approaches, decision-makers make use of different epidemic models. Here, simulation models are most common [Duijzer et al., 2018]. Simulation models can be used to study the impact of different allocation strategies for a specific epidemic. This research applies makes use of an Agent-Based Modelling Simulation (ABMS), which is a popular simulation method for studying vaccine allocation strategies [Dalgıç et al., 2017] and can be effective decision-making or policy-making tools [Dalgıç et al., 2017; Ajelli et al., 2010]. A strength of simulation models is its ability to capture realistic characteristics of both a disease and its transmission and a population. Therefore, simulation models suit for modelling a valid, real-world system of the spread of an epidemic with specific contextual characteristics [Duijzer et al., 2018], like a refugee camp. This is needed, as section 2.3.3 already highlighted the importance of contextual characteristics in studying different vaccine allocation approaches. Chapter 4 goes into deeper detail on how this ABMS conceptualized for this research.

SEIR Transmission Model

To model the transmissions of COVID-19 in a refugee camp, a SEIR Transmission model can be applied. Traditional SEIR models[2] are a popular structure for modelling the transmission of a disease Biswas et al. [2014]. The structure covers different states, in which people are susceptible (S) to, exposed (E) to, infected (I) by or recovered (R) from an infectious disease [Li and Muldowney, 1995]. To include vaccines in this transmission model, Foy et al. [2021] proposes an extended SEIR model, as presented in figure 2.1. This model is described the structure of an transmission model of an infectious disease, covering different infection stages. Derived from the traditional SEIR model, the infected stage (I) is replaced by an asymptomatic (A) and symptomatic (I) infection stage. Aslo, a stage of isolation (Q), death (D) and being vaccinated (V) are added. Therefore, this research covers six infection stages (i.e. S, E, A, I, Q, R) and three stages influencing infections (i.e. Q, D, V). By extending the traditional SEIR model accordingly, vaccination allocation strategies can be studied [Foy et al., 2021].

2 or similar, such as a more simplified SIR model [Ball and Lyne, 2006] or a more detailed SEAIQR model Foy et al. [2021]

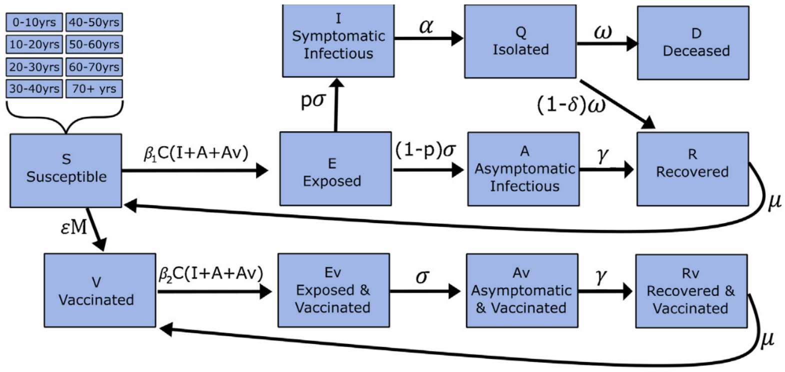


Figure 2.1: An epidemic model for COVID-19 transmissions [Foy et al., 2021, p.433]

2.4 SYNTHESIS ON HOW LITERATURE IS USED

Insights from this literature review are used to academically ground this research. From the research gap which was identified in this literature review (as introduced in chapter 1.2), four sub-concepts come forwards which are further conceptualised and integrated in following chapters, to study their dynamics. Next sections explain how these concepts are used in this research. These concepts are more specifically introduced and conceptualised in chapter 4.

2.4.1 Concept 1: Interactions in an Open-system refugee camp in this research

As explained in section 2.2.1, refugee-host interactions can be studied through four factors. In this research, the interactions between refugees and host communities are studied with a specific focus on the location of the interaction (factor 2) and the ratio of refugee-host communities (factor 3). Namely, these two factors allow for studying the link between their interactions and the spread of COVID-19 inside and around refugee camp settlements. The type of economic activity (factor 1) and the additional type of interaction (factor 4) do not influence COVID-19 contagions, so these factors are left out of scope. How factor 3 & 2 influence COVID-19 contagions is explained in next section.

2.4.2 Concept 2: Restricting COVID-19 measures in this research

The impact of restricting COVID-19 measures, as discussed in section 2.2.2, implicitly reduce the number of refugee-host interactions, triggered by two things. On one hand, lockdown-restrictions affect the openness of the refugee camp and in-camp facilities, and therefore refugee-host interactions. On the other hand, movement restrictions inside the camp and compliance to measures affects interactions among refugees themselves. In this research, camp openness which decides the possibility of refugee-host interaction is reflected by different levels of lockdown-measures: (1) an unconditional lockdown, (2) a conditional lockdown and (3) no lockdown. These lockdowns also guide the openness of in-camp facilities which can be controlled by the Bangladesh Government (i.e.the vicinity market). For other, more informal and uncontrollable measures inside the camp, formal regulations are practically infeasible. Therefore, a factor of individual compliance to live-up with behavioral rules are considered: (1) complying to stay-at-home when being sick and (2) comply to only visit public places in being vaccinated.

2.4.3 Concept 3: Vaccine Allocation in this research

To measure the effect of different vaccine allocation strategies, elements from the literature review and practical insights on vaccine allocation in refugee contexts are used. A first important element is *vaccine scarcity*, which is used as a basis for the number of vaccines which can be allocated at a certain point in time. A second element which is applied is the *interval of vaccine deliveries*, which defines when different vaccine batches arrive to be allocated. Lastly, a vaccine allocation mechanism is applied from literature which defines the different vaccine allocation strategies. For this, demographic age-based elements from the Rohingya and Bangladesh populations are used to define prioritization groups, as they have different demographic characteristics [Bhatia et al., 2018]. Four age-based sub-groups are defined: children (< 18 years), young adults (18-40 years), older adults (40-60 years) and elderly (> 60 years).

2.4.4 Concept 4: A COVID-19 transmission model in this research

For each age group, different infection stages are defined through an extended SEIR-model structure: in this research, individuals from both the refugee and host community population are assumed to be susceptible to a COVID-19 infection (S). After becoming exposed to COVID-19 (E), an individual stays asymptomatic (A) or symptomatic (I) to the infection. It is assumed individuals who become symptomatic isolate (Q) themselves. In isolation, an individual either recovers (R) or dies (D). In case of being vaccinated (V), individual's chance of becoming infected (A or I) by COVID-19 is lower. However, two realistic scenarios are considered regarding vaccinated individuals: vaccinated people being 1) able or 2) unable to infect others. Both scenarios are still unclear [Peiris and Leung, 2020a].

2.5 CONCLUSION

In this chapter, four sub-concepts were studied in an extensive literature review. To do so, studies on relating topics were consulted, supplemented with practical insights from policy documents on the COVID-19 responses in refugee camps. An open-system refugee camp with interactions between refugees and host communities was researched, which can be defined by social, legal or economic interactions between both populations, inside or outside refugee camps. This research builds forth on economic interactions, as these are most frequently recognized in context of the Rohingya camps. Also, the impact of COVID-19 and following measures were researched. Here, it was concluded refugees have become even more vulnerable, caused by lockdown measures, in-camp movement restrictions and the practical implications of compliance with measures in refugee camps. To release the burden of contact reducing measures, vaccines and vaccine allocation were researched. Summarized from this, most influential factors for effective vaccine allocation relate to vaccine *scarcity*, an *allocation strategy approach* and what *objective* is considered to be reached with the prioritizing of people. In chapter 3, a research design is presented as a first step to translate insights to a system of study for this research.

3 RESEARCH DESIGN

Chapter 3 presents a research design for answering the main research question. This research question is structured by raising six sub-questions, as presented in section 3.1. To answer these research questions, a research starting point is presented in section 3.2. Furthermore, the research approach is presented in section 3.3. Lastly, a research methodology in line with the formulated approach is described in section 3.4.

3.1 MAIN RESEARCH QUESTION & SUB-QUESTIONS

This research answers to the following main research question: *What vaccine allocation strategies can be identified as an effective trade-off between allowing individual interactions and controlling COVID-19 infections in an open-system refugee camp settlement?*

To answer this question, six sub-questions are set-up:

- **Question 1:** What drives interactions in an open-system refugee camp settlement, influenced by restricting COVID-19 measures?
- **Question 2:** How can different vaccine allocation strategies be defined in context of a refugee camp settlement?
- **Question 3:** How can interactions in an open-system refugee camp settlement, vaccine allocation strategies and being vaccinated to COVID-19 be conceptualized and formalized in line with an existing infectious disease (SEIR) model?
- **Question 4:** How can this formalised concept be integrated with an existing agent-based model on COVID-19 infections in refugee camp settlements?
- **Question 5:** How can the dynamics between COVID-19 infections in an open-system refugee camp settlement and vaccine allocation strategies be explained with an agent-based experimental simulation study?
- **Question 6:** How can the outcomes of this study be translated to an effective strategy for COVID-19 vaccine allocation in a refugee camp?

3.2 A RESEARCH STARTING POINT

As a starting point for answering these questions, an existing model for the spread of COVID-19 in a refugee camp is used on which this research builds forth, constructed by Nering Bögel [2020][1]. This model reflects a stylistic, isolated refugee camp environment, in which refugees interact with other refugees. Here, refugees visit food collection points and water, sanitation and healthcare facilities. By concentrating in these areas, interactions take place, potentially resulting in a COVID-19 transmissions. In this model, COVID-19 transmissions are modeled through an extended version of the SEIR-structure (as introduced in chapter 2), as infections (I) are further defined through asymptomatic infections (A) and symptomatic infections (I). Other characteristics of this model are related to COVID-19 measures, such as movement restrictions, usage of face-masks and compliance to stay-at-home measures. This model is used as a starting

1 This model can be found on https://github.com/MeykeNB/Covid-19-in-refugee-camps

point for this research. To build forth on this model and apply the different concepts as introduced in previous chapters, three general adjustments are made to the model: **First adjustment: add camp openness** - A first adjustment is to add a component to the model to create openness of the camp blocks, by adding a host community population which can visit the camp environment. This adjustment sets the basis for allowing refugee-host interactions, which reflects camp openness as introduced in section 2.2. **Second adjustment: extend epidemic model with vaccinations** - A second adjustment is to extend the transmission model with factors which allow the studying of different vaccine allocation strategies. For this, elements from a study by Foy et al. [2021] are used as a theoretical basis (see figure 2.1). The study presents a conceptual basis of a SEIR-model, including being vaccinated. To compare different vaccine allocation strategies in this research, this adjustment allows for the introduction of vaccines as an 'infection stage'. **Third adjustment: translate to case study context** - A last adjustment is to translate the existing model to a context of the Rohingya refugee camp settlements. As the existing model is stylistic, it is not applicable to a specific context. However, to study the effectiveness of different vaccine allocation strategies, context is a highly important factor [Privett and Gonsalvez, 2014]. For example, to study the effectiveness of vaccine allocation strategies, demographic characteristics of both Rohingyas and Bangladeshi can influence the COVID-19 transmitting process. Section 3.3.1 goes into more detail on the case study and in chapter 4 more context-dependent elements relating to the case study are introduced.

3.3 RESEARCH APPROACH

To conduct this research, two research approaches are chosen: the analysis of a case study and the application of ABM. Both approaches are explained in this section.

3.3.1 A Case Study: The Rohingya Nayapara Refugee Camp

Relating to the third adjustment on the existing model, a fraction of one of the Rohingya camps in Bangladesh is selected as a case study. Case studies are a useful tool to bring theoretical concepts into practice, and can be used to develop a model of a real-world system [Van Dam et al., 2012]. To study a real-world open-system refugee camp with refugee-host interactions happening here, a case study is used for creating a context-specific model which is feasible for analysis. Context-specific factors are important to create valuable insights which can be applied to the context of the Rohingya camps. This context-dependency for effective decision-making was highlighted earlier, and a case study allows to translate context-specific mechanisms which represent the Rohingya refugee camps in Bangladesh.

However, as the Rohingya camps host up to 1 million people, it is not feasible to study the entire system. It is unfeasible to construct and efficiently analyse a model which covers the full size of the Rohingya camps, so some criteria are set-up with the aim to pick a smaller fraction of the Rohingya camps which represent their population and on which the concepts can apply which demarcate the scope of this research. A case study is selected through the following criteria and availability of up-to-date data on:

- Clear geographical boundaries of the camp site
- Interactions between refugees and hosting community
- An existing market & other facilities both population interact
- Separate living areas for refugees and host communities

Firstly, geographical boundaries allow for physical identification of a system. Secondly, interactions between refugees and host communities need to be allowed in this system, as this reflects the open-system refugee camp. To study their interactions, information is needed on where these interactions happen (i.e.where shared facilities locate, such as markets or in-camp shops). Separate living areas allow for studying the effect of lockdowns and movement restrictions between both populations.

According to these selection criteria, a sub-block of the Nayapara Refugee Camp (RC) has been selected as a case study (see figure 3.1). Nayapara RC is one of the Rohingya Refugee camps in the Bangladesh Cox's Bazar Region, and locates close to host communities from Bangladesh. The camp can be sub-divided in different sub-blocks, which define its smallest administrative sub-units (as defined by UNHCR). One of these sub-blocks is studied, where around 900 Rohingyas are estimated to live. Sharing a shelter with their family members, the people here form a small community, headed by community leaders (called *mahjis*).

This sub-block has been selected as it characteristics meet with the selection criteria described earlier: the Nayapara camp block's geographical boundaries are clearly defined and is located close to the host communities. Along the road of this camp, a big market is located, which is the main basis of interactions between these Rohingyas with the host communities. Also, inside the camp various economic activities exist [Rosenbach et al., 2018]. This indicates intensive interactions between Rohingyas and Bangladeshi, both inside and along the borders of the camp. However, the two populations still live separately, which is needed to study the effect of a lockdown imposed for the camp.

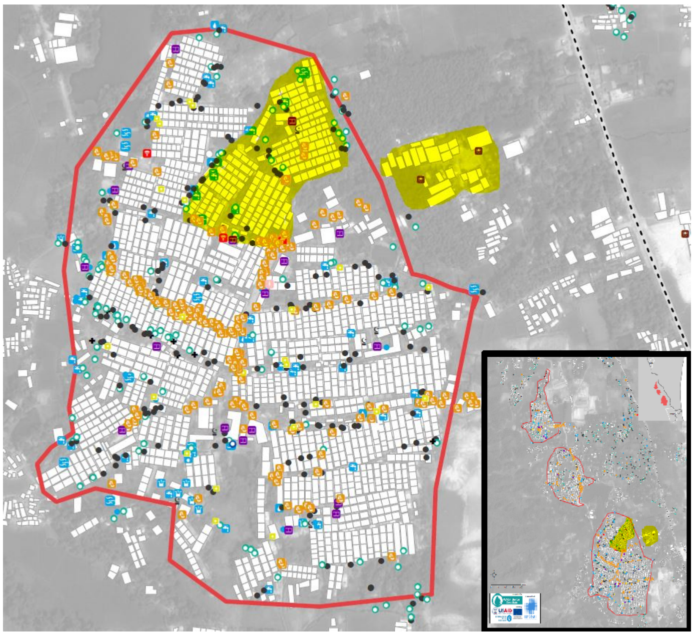


Figure 3.1: The Southern Nayapara RC Blocks

Case Study Data & Information Sources

In general, data on this case study is obtained from different sources. An overview of data & information sources is presented below:

- **Literature** is studied on the economic structures in and around the Rohingya settlements. Here, two scientific papers are used.
  - Filipski et al. [2020] gathered survey data on 326 local businesses in and outside the Kutupalong region. The paper presents information on the economic interactions between Rohingyas and the host community of Bangladesh, their demographic characteristics, the economic activities and insights on income-generating performance.
  - Bhatia et al. [2018] gathered survey data on primary needs of Rohingyas who have recently arrived in Bangladesh (which is needed for this case study as the X camp settlement hosts recently arrived refugees). This paper also discusses needs of the host community households.

- **Open source data** was consulted on the Rohingya refugees in Bangladesh. An overview of these data sources:
  - HDX presents data on needs for both Rohingyas and Host Communities and population data per camp settlement
  - UNHCR data presents a Joint Multi Sector Needs Assessment for the Rohingyas before and after COVID-19. From this, data on reduced income-generating needs is obtained
  - The Government of Bangladesh presents data on local markets and mobility between refugee camp settlements and host communities
- **Interviews** were conducted to validate and fill information gaps, with experts on the Rohingya refugees in Bangladesh. Here, three experts were interviewed with a background at UNHCR. Information obtained from these interviews can be found in appendix B.

3.3.2 An Agent-Based Modelling Approach

This research uses an ABM-approach for defining and decomposing the system of study. ABM allows for studying interactions and behavior of different entities, which are simplified versions of 'things' representing the 'real world' [Van Dam et al., 2012]. In this research, these 'things' are elements from the sub-concepts as discussed in chapter, translated to the context of the Rohingyas. In other words, the physical things in the open-system refugee camp environment are modeled which reflect the real world observations derived from the case study. In ABM, elements are modeled through three core anatomies: **agents**, an **environment** and **time** [Van Dam et al., 2012].

Agents can represent different entities, ranging from individual human beings to representations of groups, organizations or nations [Van Dam et al., 2012]. Agents show certain goal-oriented behavior [Jennings, 2000], which is an aggregation of the agent's actions and internal structure [Van Dam et al., 2012]. This research distinguishes between two types of actors: refugees and people from host communities. Both actors have a set of daily activities, which are their basis for interacting with other individuals. **Refugees** live inside the boundaries of refugee camp environment, and follow their individual activity schedule. **People from host communities** also have a daily activity schedule, which expresses in entering the camp environment on a daily basis. Based on different levels of camp openness and influenced by their state of health, host community people (cannot) visit the camp.

Agents are in interaction with the **environment**, which is the external physical and non-physical space in which agents perform their behavior. The environment contains information and a structure. The information agents obtain from the environment changes their internal state, making these agents perform certain actions. The structure of the environment defines an agent's situation in relation to other agents, in networks and over space [Van Dam et al., 2012]. This research distinguishes between two types of environments: a physical camp environment and a non-physical environment. The **physical camp environment** defines in which geographical space refugees and people from host communities interact with each other. For example, the physical environment is reflected by shelter sites, main roads crossing the camp site, an entry point of the camps and places where people interact. The **non-physical environment** defines all information which structures the behavior of refugees and host community people, such as information on camp openness, in-camp movement restrictions and the prioritization of vaccines. For example, visitors are not allowed to enter the camp in case of a lockdown, which influences the host communities decision/ability to enter the camp.

A last anatomy for is **time**. ABM uses discrete time steps, triggering the interactions among agents and with their environment [Van Dam et al., 2012]. In this research, four time resolutions are used: minutes, hours, days and weeks. Specific times through these three dimensions trigger the moment on which agents decide to execute an activity. For example, refugees fulfill their needs by going to a local market at a specific time of the day. As time steps are triggered per minute, this research uses an operational time scale, which allows for decision-support on operational levels [Van Dam et al., 2012]. This time frame is chosen as it most validly represents a infectious virus transmission process. Namely, a transmission of COVID-19 from one individual to another individual depends on how long a susceptible interacts with an infectious person. For COVID-19, interaction with an infected individual for longer than 15 minutes is considered enough for an infection [Chu et al., 2020].

3.4 RESEARCH METHODOLOGY

3.4.1 A Step-based methodology for a Complete ABM Study

As a methodology for conducting this research, the case study & ABM approach are applied through a step-based modeling approach as proposed by Van Dam et al. [2012, p.98]. They propose 10 steps to conduct an ABM study, which are as follows: (1) Problem formulation and actor identification, (2) System identification and decomposition, (3) Concept formalisation, (4) Model formalisation, (5) Software implementation, (6) Model verification, (7) Experimentation, (8) Data analysis, (9) Model validation and (10) Model use. These steps are used to structure the methodology for answering each sub-question. In figure 3.2, an overview of the visual summary of the structure and time path for this research is shown. In the next section, each a methodology for each sub-question is explained and linked to these steps. Also, the figure guides the general structure of this report in general. With all these steps followed, a complete and structured basis is set for this study. For a more detailed version for this research plan, see appendices A.1 and A.2.

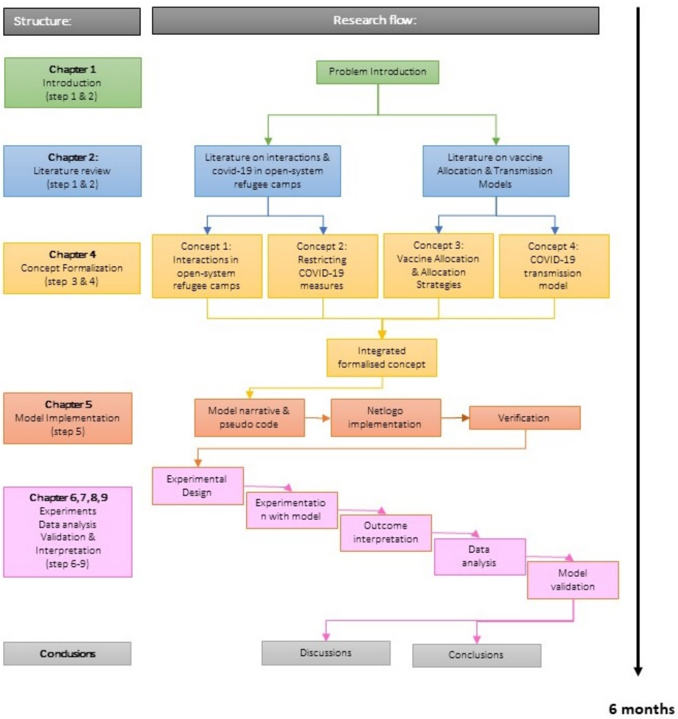


Figure 3.2: Research Flow Diagram & Time Schedule

3.4.2 Methodologies for sub-questions

Trough the ABM-structured steps, each sub-question is answered as follows:

Sub-question 1: What drives interactions in an open-system refugee camp settlement, influenced by restricting COVID-19 measures?

To answer the first research question, a combination of literature studies and expert interviews are conducted. The interactions between refugees and host communities are first researched in literature without the context of COVID-19. Different academic papers are studied on refugee-host interactions, with a focus on why and how refugees interact with the host community. This is done on two levels: firstly, a general search is done, for different refugee camp contexts. In this way, a broad understanding on refugee-host interactions is created. Secondly, literature on refugee-host interactions are studied with a specific focus on the Rohingya refugees in Bangladesh. By combining both levels of literature, an academic basis is created for understanding the refugee-host interactions in line with the case study on the Rohingya refugees. A second branch of literature is then studied on the impact of COVID-19 in refugee camps, and how it affects the refugee-host interactions. Again, a general literature study is performed first. Then, specific literature on the Rohingya refugees is studied. Taking general refugee-host interactions as a basis, literature is studied on the following subjects: 1) the effect of the spread of COVID-19 and following restricting measures on the freedom/ability to interact, 2) the following shifts in needs and vulnerability of individuals and 3) how individuals behave as a reaction to these restrictions In this way, it is studied how interactions were influenced by COVID-19 from a bottom-up, refugee perspective. To finalize the answer to this research question, expert interviews are conducted. Experts are interviewed with experience on the Rohingya refugee camps. The information derived from these interviews is used to validate the answer formulated with literature, and to fill missing gaps which cannot be answered or found in literature. By answering this question, a basis is created for conceptualizing and formalizing refugee-host interactions and how these are influenced by COVID-19 and its following measures, from a refugee perspective. In the ABM-structure, this covers the first part of step 1 & 2.

Sub-question 2: How can different vaccine allocation strategies be defined in context of a refugee camp settlement?

To answer the second research question, a combination of literature studies, desk reviews and expert interviews are conducted. Literature on vaccine allocation is studied in general first, with a focus on the following subjects: 1) a definition of vaccine allocation, 2) existing models for vaccine allocation, 3) vaccine allocation strategies and 4) its factors describing the performance of a particular strategy. Here, a general understanding is created on vaccine allocation and what academic research has been performed on this topic. This gives a general basis of vaccine allocation from an academic perspective. This is needed, as current literature does not discuss vaccine allocation strategies which can be applied explicitly on refugee camp contexts. With this theoretical and academic foundation, vaccine allocation strategies are studied for a refugee camp context. Here, a combination of literature studies and desk research is performed. Literature is studied on vaccination programs in refugee camp contexts from other epidemics which happened prior to COVID-19 and for COVID-19 when available. Desk research is performed on vaccine allocation as a part of COVID-19 response programs, raised by national governments and other mandated organizations. For example, the vaccine allocation strategy of the Bangladesh Government is studied through official policy documents. Also, vaccination allocation programs in developing countries are studied through documents of officially mandated organizations, like the UNHCR & WHO. When different vaccine allocation strategies are formulated through the above described research methodology, they are finalized and validated with expert interviews. For this, experts with knowledge on vaccinations programs in the Rohingya camp settlements are consulted. By answering this question, a basis is created for conceptualizing and formalizing different vaccine allocation strategies which can be applied on a refugee camp, from a perspective on the COVID-19 response coordinator. In the ABM-structure, this covers the first second of step 1 & 2.

Sub-question 3: How can refugee-host interactions in an open-system refugee camp settlement, vaccine allocation strategies and being vaccinated to COVID-19 bet conceptualized and formalized in line with an existing infectious disease (SEIR) model?

To answer the third research question, refugee-host interactions and vaccine allocation strategies need to be conceptualized first. As this research builds forth on an existing model for the spread of COVID-19 in a refugee camp, these concepts are constructed correspondingly to this model. To do so, a first step is to conceptualize each sub-concept separately: a sub-concept is defined for refugee-host interactions, for vaccine allocations strategies and for the spread of COVID-19. Each sub-concept is conceptualized by defining the inner relations and the ABM-structured anatomies. Inner relations describe how the different factors within the sub-concept relate and behave, which is done by constructing several flow and causal relation diagrams. Both can be used to conceptualize and communicate cause-effect relationships between different sub-systems or factors [Bala et al., 2017]. ABM-structured anatomies structure each factor in the sub-systems, as either an agent or as a part of the external environment. For each factor, properties, actions and relations are defined with the use of a Unified Modeling Language (UML) diagram. In these diagrams it is possible to structure objects into a modeling language [Dobing and Parsons, 2008]. When each sub-concept is conceptualized, an integrated sub-system is created as an aggregation of these ABM-structured sub-systems. Again, UML is used here to visualize the integrated concept of refugee-host interactions, different vaccine allocation strategies and the spread of COVID-19 in a refugee camp. Secondly, the conceptual model is formalized. Here, the integrated concept will be made context-specific, i.e. by defining context-specific information for each agent (and their behavior and relationships) and the environment in which they operate. To quantify each conceptual component in the model, data and information from the case study is used. This data is obtained from desk research, data-sources and literature on the case study camp settlements. In the ABM-structure, this covers step 4. By answering this research question, a formalized concept is constructed, describing refugee-host interactions, the influence of COVID-19 and different vaccine allocation strategies. By formalizing this concept with information from the case study on the Rohingya refugee camp settlements, this sets a basis for creating a context-specific model. The complete answer to this research question covers step 3 & 4 in the ABM-structure.

Sub-question 4: How can this fomalized concept be integrated with an existing agent-based model on COVID-19 infections in refugee camp settlements?

For answering the fourth research question, the formalized concept is translated and implemented into an ABM-supported language and verified afterwards. Firstly, this is done by creating a narrative story for the model and by formulating this into a pseudo code. The narrative story is a first step of translating the formalized concept from the previous step into a computational model. Here, a story is created for each agent and the environment, how agent behave and when they changes their behavior. The story narrative will be based on the temporal structure of the existing model which this research builds forth on: time is structured by minutes. This means, a narrative is constructed for each minute on the day where something happens inside the model. For example: when an individual wakes up, when that individual goes to a local market and how long it takes to get infected by COVID-19. In this way, a time-specific model is created giving best insights in the infection processes for refugees. Secondly, pseudo-coding is used to translate this narrative into the programming language, but yet in a comprehensive way: pseudo-coding is the last step before translating the model into Netlogo, a computer-based program for ABM implementations. After the model is implemented in Netlogo, it is verified. Model verification is done to check if all model structures perform according to the modeler's ideas. For verification, at first single agents and their behavior are tested through single-agent testing. After, the model behavior is verified by studying interactions between agents and the environment through Interaction testing in a minimal model. The model is ready for its use by completing this sub-question. By doing so, it covers step 5 & 6 in the ABM-structure.

Sub-question 5: How can the dynamics between COVID-19 infections in an open-system refugee camp settlement and vaccine allocation strategies be explained with an agent-based experimental simulation study?

To answer this question, three main activities are performed: 1) the design and execution of an experimentation design, 2) data analysis and 3) model validation. Firstly, an experimentation design is created. This design consists of different hypotheses, formulated from the expected results of policy measures relating to vaccine allocation strategies. For example, a hypothesis is formulated as follows: "Vaccinating most vulnerable people first will lead to most effective reduction of COVID-19 contagions". Next to the formulation of these hypotheses, a time frame is chosen for the experiment. This time frame is chosen based on how long the model needs to run minimally, to be able to study how COVID-19 infections take place. For example, it considers the minimal time to become exposed to -, be infectious to others and to recover from COVID-19. As a third part of this experimentation design, different scenarios are set-up. Scenarios allow for testing different hypotheses in different real-world conditions. To execute each experiment, several input parameters are selected and used to run the model. For this, a random value for each parameter is chosen to replicate runs in the model over different inputs. Secondly, the model results from the experiments are analysed with data analysis. To compare outcomes of different experiments, the model outcomes are first studied without applying a vaccine allocation strategy. This creates a basis for comparing different strategies, which is done by visualizing and identifying patterns in model outcomes and by interpreting these from the perspective of refugees and the emergency coordinator. After the basis outcomes of the model are clear, the experimental design is applied on the model. For each experiment, different hypotheses are tested and the outcomes from the model are interpreted. Here, a special focus is set on data analysis regarding: data exploring, visualizing patterns and interpreting and explaining these results. Thirdly, model validation is done as a final step for this question. The outcomes of each experiment will be presented to experts which were initially interviewed for sub-question 1-2. Also, the outcomes of different vaccine allocation strategies will be compared to comparable analyses of other vaccine allocation programs. For this, literature studies will be used. With a valid model, general conclusions can be derived from the model results. The model is ready for its use by completing this sub-question. By doing so, it covers step 7, 8 & 9 in the ABM-structure.

Sub-question 6: How can the outcomes of this study be translated to an effective strategy for COVID-19 vaccine allocation in a refugee camp?

To answer this question last sub-question, the outcomes from previous sub-question are interpreted and explained. Here, the general aim is to translate the outcomes of the experiments into decision-making information, which can be used by the emergency response operator. This means, for different vaccine allocation strategies, the model outcomes are summarized, explained and ranked. Also, a critical reflection on each experiment is presented as an offset to the strategies which have been studied. By answering this question, a full set of vaccine allocation strategies are studied and interpreted from the model and translated to informative decision-making advice. By doing so, it covers step 10 in the ABM-structure.

3.5 CONCLUSION

In this chapter, a research design was formulated. Based on six sub-question covering the main research question, a starting point was explained for this research. An existing model for the spread of COVID-19 is used, which is adjusted/expanded for (1) camp openness, (2) a vaccine allocation mechanism and (3) the Rohingya Refugee camp context. The research which structures this approach is agent-based modeling, which is a discrete model which allows for studying individual behavior of refugees in an refugee camp environment. To construct the agent-based model with a contextual link to the Rohingya refugees, data and information from one of the sub-blocks of the Nayapara Rohingya Refugee camp are used. Lastly, a methodology was proposed for constructing, analysing and using the model. Here, 10 steps for an ABM study are set as a structural guidance for a complete and meaningful research. In chapter 4, a first step for model construction is made as this chapter is dedicated to translating the insights from the literature review to an integrated and formalized concept.

4 CONCEPT FORMALISATION

Chapter 4 gives an answer to sub-question 3 of this research: *How can interactions in an open-system refugee camp settlement, vaccine allocation strategies and being vaccinated to COVID-19 be conceptualized and formalized in line with an existing infectious disease (SEIR) model?* First, a basis for conceptualization and formalization is explained in section 4.1. Secondly, the research question is broken down into different sub-concepts, which are conceptualized and formalized separately in section 4.2. Next, these sub-concepts are integrated to one formalized concept in section 4.3. The chapter ends with an overview of model assumptions in section 4.6 and a conclusion in section 4.7.

4.1 SYSTEM IDENTIFICATION & DECOMPOSITION

"Systems are not actual entities, as such, but are idealisations or abstractions of a part of the real world" [Van Dam et al., 2012, p.17]. An abstraction of the system of study is depicted in figure 4.1. The figure shows an Unified Modeling Language (UML)-based representation of this system, covering the four main concepts which together aggregate to the open-system refugee camp.

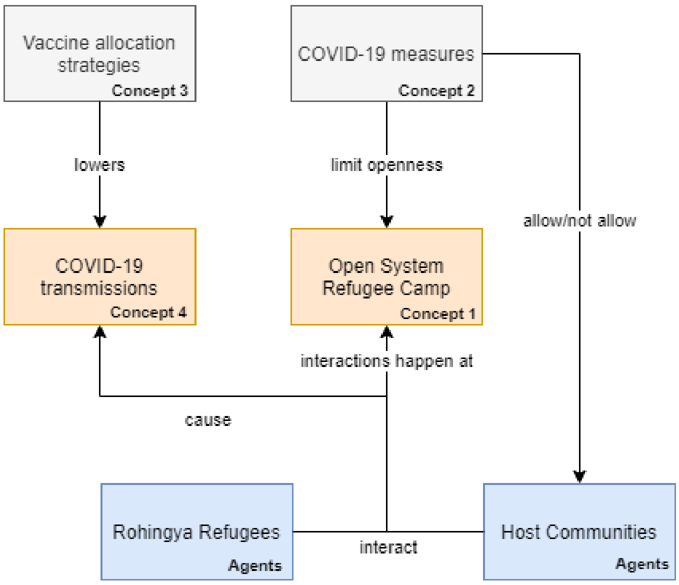


Figure 4.1: An open-system refugee camp, influenced by COVID-19 and vaccine allocation

The system is describes agents (Rohingya refugees & host communities), and the physical (the open-system refugee camp) and non-physical environment (i.e. COVID-19 measures & vaccine allocation strategies) in which these agents interact inside the refugee camp. As both populations live in separate areas, the interactions between the two happens on locations where they mix. The refugee camp is defined as the physical environment, where COVID-19 transmission happen as a result of interactions. This links to the non-physical environment, which is a structure of government-lead COVID-19 measures and COVID-19 vaccine allocation. COVID-19 measures result in the level openness of the camp itself and of markets here, as a means to reduce interactions. Vaccine allocation serves as a potential balancing mechanism: the allocation of vaccines can have a negative effect on the number of COVID-19 infections which happen on interactive spots in the camp environment.

4.2 CONCEPTUALIZATION & FORMALIZATION OF SUB-CONCEPTS

"Systems always consist of multiple components, usually guided by the structure of a system" [Van Dam et al., 2012, p.17]. Sub-concept are conceptualized and formalized as a first step for constructing a model of the demarcated system. To do so, an ontology has been developed for several sub-concepts. An ontology can be defined as a combination of a conceptualizing and formalizing [Gruber, 1993], and are typical for case studies using ABM [Van Dam et al., 2012]. Through the ABM core anatomies, introduced in chapter 3.3, sub-concepts are further specified as either an agent (or an agent's specific behavior or interaction with other agents) or as the environment (both physically or non-physically, containing the information absorbed by or structure demarcating the behavioral space of agents) [Van Dam et al., 2012].

4.2.1 Concept I: Conceptualization of refugee-host interactions in an open-system refugee camp

Part I: Refugee-host interactions

As in this research the aim is to use an COVID-19 transmission model, refugee-host interactions have been conceptualized based on other studies which used an SEIR transmission model in combination with an ABM model. A number of these studies conceptualize interactions as an agent's execution of daily activities or other daily routines (e.g. Hailegiorgis and Crooks [2012], Crooks and Hailegiorgis [2014], Rajabi et al. [2016]). In this research, daily activity schedules serve as a concept for agent behavior and interaction, of which a flowchart concept can be found in appendix D.1.1. This concept represents time-based flows of activities executed by individual agents on a daily basis: when an agent wakes up, different activities follow, based on an agent's population and age. Each activity represents a location and moment where Rohingyas interact with Bangladeshi or with other Rohingyas. Based on insights from expert interviews who work in the Rohingya camps and supplemented with insights from literature, an summary of a Rohingya activity schedule is made.

Daily activities of Rohingya refugees
Rohingyas are active during the day. In the morning, Rohingya children below 14 years old go to Temporary Learning Centres (TLCs), which are in-camp education centres. Also, mosques are used for education for children [Interview 1, 2021; Interview 2, 2021]. Whereas children go to school in the morning, the older people from both the Rohingya & Bangladesh population visit a mosque. Mosques serve as a location where both Rohingyas and Bangladeshi practice their religion on a daily basis. As 90% of the Bangladeshi and all Rohingyas are Muslim [Population of the World, 2021; Mohajan, 2018], mosques are considered the main basis of religious practices inside and around the camps. Inside the refugee camps, a mosque exists for each sub-block inside a block. Also, some bigger mosques exist outside the camp boundaries, which are usually bigger and more mixed between the two populations [Interview 2, 2021]. After a morning pray, the elderly usually return home or go to a local market, where they socialize and charge their phones. Rohingya adults and children visit markets as well, but are also busy to generate the essentials for their households: they collect water and food at sanitation/water taps and food collection points. Thereafter, Rohingya adults and Bangladeshi go to local markets, where they interact by trading, selling small things or socialize as well. These interactions are really informal, and shops and markets do not have predefined spots. In the end, the main reason for elderly to visit markets and in-camp facilities is to socialize, whereas adults and children go here to sustain the livelihoods of their families [Filipski et al., 2020]. At the end of the day, all Rohingyas go back to their shelters and host communities are demanded to leave the camp site. Not many more interactions happen until the next day: due to a lack of electricity, camp sites are barely illuminated. Therefore, most of the people stay home.

From these activities, an activity schedule has been defined for both populations. Here, the main focus is set on the *refugee-host interactions* and where these take place. As many different types of other interactions happen, which would make the model quite computational, interactions are conceptualized by three different types: in-camp interactions among Rohingyas, in-camp refugee-host interactions and refugee-host interactions at the vicinity market. **In-camp interactions among Rohingyas** represent all interactions which relate to the daily execution of things outside shelters, such as collection of water, food, visiting sanitation facilities and religious buildings. An activity left out of scope from this model is visiting a healthcare facility. As this research focuses on transmissions of COVID-19, it is assumed healthcare facilities are no source of causing transmissions, but rather a treatment facility for individuals who are already infected. **In-camp refugee-host interactions** relate to all in-camp interactions between the Rohingya and host community population. These concentrate at small, mostly in-camp markets or at meeting-points along the roads. **Refugee-host interactions at the vicinity market** are interactions which happen at the bigger vicinity market, which locates on the camp boundaries along the main road of the camp.

Locations of these in-camp facilities are conceptualised by indicating their *location* and *capacity*: the location indicates *where* people interact and the capacity regulates *how many* people interact at one place. Locations of facilities were derived from Ahmed et al. [2020], who presents an overview of the infrastructural division of public places in the Rohingya refugee camp settlements. Also, a map by Humanitarian Response [2017] is used, which was depicted earlier in figure 3.1.

Part II: An Open-system refugee camp

Agents are active inside a physical environment, which is the concept of the open-system in which interaction happen. To structure this environment, physical elements are studied from the Nayapara refugee camp: the physical structure of the refugee camp environment with different activity locations, shared facilities and shelters. These elements are depicted in the physical environment conceptualization in figure 4.2.

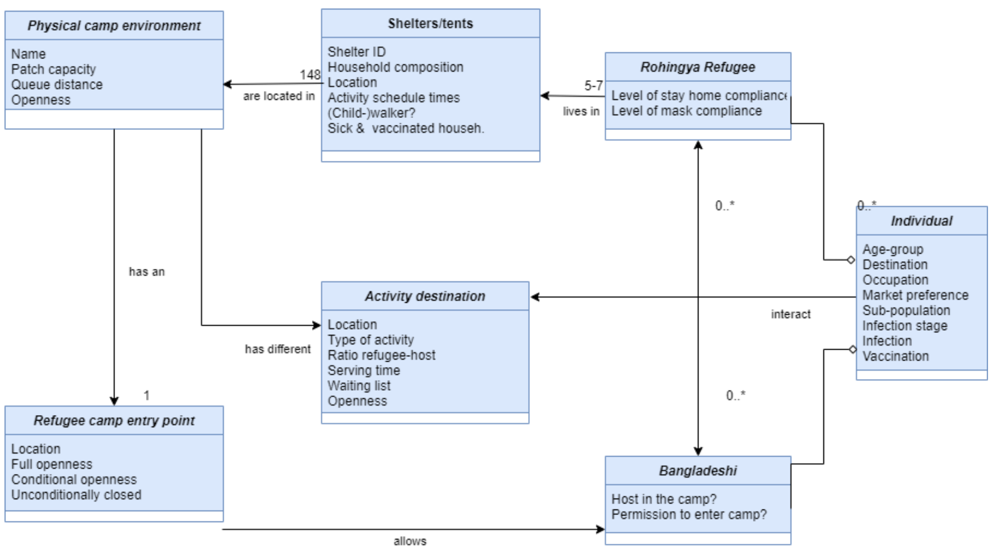


Figure 4.2: UML-based Physical Environment

Physical camp environment: Nayapara RC is located in the Teknaf district of Cox's Bazar, and borders the host community living areas. The area is densely populated, with over 22.000 refugees (in 4435 households) [HDX Data, 2021]. The area splits in different blocks and sub-blocks as administrative units. As introduced earlier in chapter 3.3.1, one of the sub-blocks has been chosen for studying. This sub-block is shown in figure 4.3 and is the general conceptual basis for the physical open camp environment.
Entry point of the camp: Before COVID-19, no physical boundaries existed around Nayapara RC. However, the Bangladesh government strictly controls the entrance of outsiders into the camp, with gates and military checkpoints Farzana [2016]. These border controls of the Rohingya refugee camps was tightened even more since May 2020,

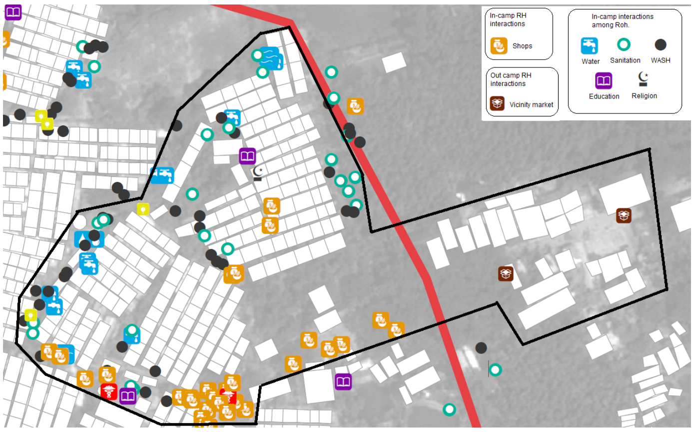


Figure 4.3: The Nayapara Block B as a conceptual basis for the physical open-system camp environment

as the government raised physical borders around the refugee camps for controlling the spread of COVID-19 [IDC, 2020]. To conceptualize the openness of Nayapara RC, an entry point is used as a formal entrance for Bangladeshi to of the camp site local Bangladeshi to enter the camp. Here, to cover different levels of camp openness/strictness of camp lockdowns, these entry points allow a number of host community people inside the camp boundaries. For example, in case of a strict lockdown no one is officially allowed to enter the camp sites.

Activity destination: Three important factors to study the interplay between interactions and COVID-19 infections are the location of interaction, the time of spending here and the number of individuals at this location. For the latter, a distinction is made between Rohingyas and Bangladeshi, by defining a ratio of visitors to a certain location. Namely, markets along borders of Rohingya refugee camps are much more mixed than in-camp markets, covering an average 12% and 50% ratio of Bangladeshi visitors respectively [Filipski et al., 2020]. For the locations of these interactions, different locations are determined where these interactions take place. For this, data is used on the general camp infrastructure from three sources: data from HDX Data [2018] and Humanitarian Response [2017] give insights in the general camp infrastructure and its facilities. Open source data from Rohingya Camp Map [2018] gives insights in public facilities (see figure 4.3).

Households & shelters: A last element used to conceptualize the physical environment is a refugee household, who live inside shelters. Shelter households are used to represent the Rohingya population inside the refugee camps. A shelter defines the living area of a household/Rohingya family, which all have a daily schedule as introduced in 4.1. For each household, a specific demographic composition and size is defined, based on current data on households inside Rohingya refugee camps in Bangladesh. This is explained more briefly in the next section. To create interaction among individuals, an activity schedule is determined for each household. For each activity, individual refugees are then created to execute this activity by moving towards an activity destination.

4.2.2 Concept I: Formalization of refugee-host interactions in an open-system refugee camp

Part I: Refugee-host interactions

The interactions between individual agents in the Rohingya refugee camps are based on daily activity schedules, which happen in the general infrastructure of the camp. Interactions happen as a result of spending time together at locations, where agents go based on their daily activity schedules. These activities have been scoped to three types of activities:

1. In-camp interaction among Rohingyas (i.e. visiting food & water points, schools, and mosques)

2. In-camp refugee-host interactions (i.e. visiting small in-camp markets & informal meeting at the streets)

3. Refugee-host interactions at the vicinity market (i.e. the bigger market along the camp boundary)

Based on these interactions, an activity schedule has been developed for each household, as shown in table 4.1.

Table 4.1: Daily activity schedules for interactions between Rohingya refugees between themselves and with host communities

	Types of activity	Location	Time	Frequency	Duration
Refugee-refugee interactions	Wake up	Shelter	8am	Daily	-
	Go to school	In camp facility	9am	Daily	1-2 h
	Visit a mosque	In camp facility	8-9am	Daily	15-30 min.
	Collect water & sanitize	In camp facility	9-10am	Daily	5-10 min.
	Collect food	In camp facility	10-12am	Weekly	1h
Refugee-host interactions	Go to a vicinity market	Vicinity market	12am-4pm	Daily	1-2h
	Go to in-camp market	In-camp markets	12am-4pm	Daily	15min.
	Go home	Shelter	4-5pm	Daily	-

These activity schedules were derived from the three expert interviews on the Rohingyas (see appendix B). Some of the activities or mechanisms behind it have been simplified: for children, schools are considered important educative centres, but are sometimes hosted in mosques. Also, marketplaces are assumed to host all economic interactions between individuals. In context of the Rohingya camp, these economic interactions are a result of various types of businesses [Filipski et al., 2020; Rosenbach et al., 2018]. However, as this research focuses on COVID-19 infections as a result of interactions, economic interactions are simplified and assumed to only happen in markets. Lastly, Rohingyas are assumed to execute their daily habits inside the camp borders. In reality, some Rohingyas are allowed to go out of the camp boundaries, but these proportions are relatively small: only an estimated 5% has a legal status to leave the camps [Rosenbach et al., 2018] and other refugees have no access to work or property outside the camps [Yesmin, 2016; Zetter and Ruaudel, 2016]. Therefore, economic interactions outside the camps are left out of scope for simplicity. Lastly, as multiple locations of the same activity can exist (e.g. there are multiple markets, schools, mosques, etc.), the choice for one of these activities is based on distance or on a social-mixing matrix. For schools, mosques, water & food points and isolation centres, the closest facility of that type is chosen. For example, children choose to go to school most closely to their shelter.

Table 4.2: Mixing patterns between Rohingyas and Bangladeshi in-camp markets vs. on vicinity markets, based on estimations by Filipski et al. [2020]

	In-camp markets	Vicinity market
Rohingyas	49%	51%
Bangladeshi	12%	88%

For market visiting, a social mixing matrix is guiding individual's destination (see table 4.2). In this way, social mixing is represented between Rohingyas and Bangladeshi, based on estimations by Filipski et al. [2020].

Part II: An Open-system refugee camp

To formalize the physical camp environment and different activity destinations inside the Nayapara B Block, two physical maps of the camp infrastructure have been studied from Rohingya Camp Map [2018] and Humanitarian Response [2017]. These maps contain accurate and up to date information about different types, frequencies and locations of facilities and market centres inside the Nayapara B block. An overview of this is presented in table 4.3. To formalize shelters and households, data from HDX Data [2018] and a study on household compositions by [Bhatia et al., 2018] are studied. Rohingya households are characterized by a household composition, which in this research is characterized by age and size: a household consists of children, younger adults, older adults and elderly. Each household is assumed to host 5, 6 or 7 individuals, adapted from data from Lopez-Pena et al. [2020] who conclude a median of six household members in Rohingya shelters. Table 4.4 shows an overview of these data.

Table 4.3: Formalization of type & number of facilities in the Nayapara RC Block B

Facility location	Frequency
In-camp markets	7
Vicinity market	1
Mosques	3
Water taps	55
Schools	4
Food collecting points	1

Table 4.4: Formalization of estimated population size & household composition in the Nayapara RC Block B

	Rohingyas	Bangladeshi
Population	950	280
Shelters	148	-
Median household (hh) size	6	5
Children per hh <18 y	65%	50%
Young adults per hh 20-40 y	20%	25%
Older adults per hh 40-60 y	10%	20%
Elderly per hh >60 y	5%	5%

4.2.3 Concept II: Conceptualization of Camp Openness

Three types of camp openness are conceptualised, which limit interactions in the open-system camp environment:

- An unconditional lockdown (strictly limited camp openness)
- A conditional lockdown (medium limited camp openness)
- No lockdown (no limitations for camp openness)

These types of lockdowns were adapted from Silva et al. [2020], and are translated to a concept of camp openness for both the camp's *borders* and its *facilities & markets*. Nayapara RC is strictly controlled by checkpoints and entry points, to regulate entrances of people into the camp. If the camp closes its borders, host communities are (partially) kept out of the camp. Also, in-camp facilities can close. In this case, both refugees and host communities are (partially) not allowed here. When no lockdown is imposed, no restrictions on interactions between refugees and host communities are implemented. This means, the camp borders are not closed and both refugees and host communities have access to all the facilities and markets in the camp. For a full lockdown, host communities are kept out of the camp and the big market inside the camp is closed. This market is assumed to be able to close by the government, as it is relatively demarcated and regulated by the Bangladesh Government Interview 2 [2021]; for other in-camp facilities, no restrictions are imposed. Namely, as using these facilities is on highly informal basis, regulating these interactions is practically impossible [Interview 2, 2021]. For a conditional lockdown, restrictions are implemented after COVID-19 infections exceed a certain threshold. The latter was the case in the Rohingya camps after the strict lockdown ended in August 2020 and public facilities such as markets and mosques were accessible for both Rohingyas and Bangladeshi, but for limited numbers of visitors [Interview 1, 2021; Interview 2, 2021].

The three levels of lockdowns are used as concepts which represent the government's decisions to limit the number of contacts between people, which reduces the number of COVID-19 transmissions. By imposing these restricting measures, a first category is applied for *host country policies in refugee camp contexts*, adapted from Werker [2007]'s framework on a structure of a refugee camp. Namely, this framework addresses *restricting* and *benefiting* policies: limited camp openness is categorized as the first type, whereas the allocation of vaccines is categorized a benefiting policy. Both types of policies are conceptualized through a flow diagramming method, of which the final concept can be found in appendix D.1.2.

Next to camp openness regulated top-down, individual behavior of refugees is used as a concept representing the compliance to stick to camp openness regulation. As in-camp regulation of contacts is hard, a factor of non-compliance is used as a potential risk of individuals not complying to two types of compliance:

1. Compliance to only visit a market if vaccinated
2. Compliance to stay-at-home if infected

The first type of compliance relate to accessibility of facilities which is based on an individual's vaccination status. If an individual is not vaccinated and non-compliant, a facility is still visited. The second rule relates to stay at home when being infected by COVID-19. Here, it is assumed refugees can follow up with this rule *if they know* they are infected. Here, symptomatic infections are assumed to be be known as a COVID-19 infection by individuals, due to having symptoms. The third rule relates to wearing a mask in public, i.e.when leaving the shelter. Here, it is assumed wearing a mask in public reduces the chance of transmitting an infection.

4.2.4 Concept II: Formalization of restricting COVID-19 measures

Restricting policies related to camp openness has been conceptualized as either no lockdown, a conditional lockdown or a full lockdown. The three different levels of restrictions define if and if so how many people can visit the camp facilities, as formalized in table 4.5.

Table 4.5: Formalization of camp openness & in-camp facility capacities, based on three types of lockdowns

Type Lockdown	Openness for:	Vicinity market	In-camp markets	In-camp facilities
No Lockdown	Rohingyas	Capacity 100%	Capacity 100%	Capacity 100%
	Host community	Capacity 100%	Capacity 100%	Do not visit
Conditional	Rohingyas	Capacity Limited	Capacity 100%	Capacity 100%
	Host community	Capacity Limited	Capacity Limited	Do not visit
Unconditional	Rohingyas	Capacity 0%	Capacity 100%	Capacity 100%
	Host community	Capacity 0%	Capacity 0%	Do not visit

In case of no lockdown, host communities are free to enter the camp site and Rohingyas and host communities are free to visit all facilities. In case of a conditional lockdown, the camp is open for limited numbers of visited, ranging from 10% to 90% compared. In case of a full lockdown, the camp is closed for the host community. Also, the bigger market is closed for visiting. This means, only interactions which are informal and uneasy to regulate happen. The selection of a restricting measure for camp openness, which is done by the Bangladesh Government, is based on two approaches: a static and a dynamic approach. For the static approach, one of the three types of lockdowns yields during the studying of the model. Here, a restricting measure for camp openness is defined for 90 days. In case of a dynamic approach, the government varies with different types of lockdowns as a dynamic interplay of measures and COVID-19 infections. Here, a basic reproduction number $R0$ is used as a threshold to determine the type of lockdown, which is reassessed by the government on a weekly basis. The reproduction number is a straightforward and broadly applied concept for the justification of policy interventions related to COVID-19 [Linka et al., 2020; Fauci et al., 2020]. This number tells how many new infections are caused by a single infected individual, as captured in equation 4.1:

$$R0 = \frac{R_{weeki}}{R_{weeki-1}} \tag{4.1}$$

Every week, an assessment is carried out by the Bangladesh Government on the basic reproduction number, which is used to determine the type of lockdown which will be imposed. Below, the default thresholds of $R0$ are shown as used for this research. These are applied from Liu et al. [2020], but is should be mentioned the selection of $R0$ thresholds is contextual and subjective [Liu et al., 2020].

- $R0 < 1.0$: no lockdown
  No capacity for vicinity market, camp fully open for host community
- $R0$ 1.0-1.5: conditional lockdown
  Varying capacity for vicinity market, camp partially closed for host community
- $R0 > 1.5$: unconditional lockdown
  Vicinity market closed, camp fully closed for host community

Lastly, to formalize the concept of compliance, it is determined for each household whether they are compliant or not for stay-at-home rules or wearing-mask rules. Whether a household is compliant or not is based on the current state of lockdown. If no lockdown is imposed, households are assumed to have lower compliance (approximately 30% of all households) than for a conditional (50%) or unconditional (80%) lockdown. Here, it is assumed compliance is associated with social fear, which is assumed to grow if more measures are implemented, as adopted from Jørgensen et al. [2021].

4.2.5 Concept III: Conceptualization of vaccine allocation

In line with Werker's 2007 twofold typology of restricting and benefiting policies which can be applied by governments in a refugee context, benefiting policies are related to the allocation of vaccines. Here, vaccines serve as a benefiting factor for camp openness, as less infections are a result and the camp can remain open for longer. To conceptualize vaccine allocation, six general main elements are defined: (1) vaccine availability, (2) delivery of vaccine in different batches, (4) vaccine efficacy, (5) vaccine infectiousness and (6) the vaccine allocation approach. This concept can be viewed in appendix D.1.3. Starting with **vaccine availability**, which is conceptualized by ranging over different numbers of available vaccines. Here, expected numbers of vaccines derived from the Bangladesh's NDVP are used as a baseline: see appendix C.3. Here, it is assumed the availability of one vaccine can be injected to one individual, with a 90% or 100% **efficacy rate**. An efficacy of 90% means 10% of vaccinated individuals can still be **infectious to others**, and is chosen to be a relatively valid value in context of vaccines in Bangladesh. Namely, about 80% of 240 million ordered vaccines in Bangladesh have efficacy-rates over 90%. Vaccines are assumed to arrive through **3 delivery batches**, with intervals of 30 days. This assumption is also based on the Bangladesh NDVP, which defines different phases on numbers of expected vaccines. Here, the aim is to vaccinate a minimum of 80% of the Bangladesh population, which is applied to this concept as well. Vaccines are assumed to be allocated immediately after arrival, for which full willingness is assumed to get vaccinated by the Rohingya population. This willingness is out of scope in this research, as it is considered part of vaccine distribution, which is another phase in the vaccine supply chain, according to Duijzer et al. [2018].

Vaccines are allocated based on different **vaccine allocation strategies**. These strategies are based on the Bangladesh Government's choice of vaccine prioritization and on vaccine availability. Vaccine availability is an important factor linking to decision-making with scare vaccines, as introduced in chapter 2.3.2. Vaccine allocation is conceptualized as a mechanism of allocating the number of vaccines over individuals, based on their age-group or the level of their risk transmission profile. Age-groups guide the prioritization strategies which link to age-based demographic approaches. Transmission profiles link to transmission-based approaches, which is defined by the *force of infection* and the level of activeness by an individuals to interact with others. The force of infection depends on age, and is the rate to infect others when infected. The activeness of individuals in their share of the total population who interacts with others. Here, elderly and to some extent children are assumed not to be as active as adults. Section 4.5 goes into further detail on the vaccine allocation strategies which are compared in this research.

4.2.6 Concept III: Formalization of vaccine allocation

The concept of vaccine allocation is formalized by defining how many vaccines will be allocated (which reflects vaccine scarcity), when (reflecting the delivery of vaccine batches) and by the determination to whom vaccines will be distributed (which reflects the prioritization vaccines). To determine how many vaccines will be available, a default number of available vaccines is selected based on data from the Bangladesh NDVP (also see appendix C.3). In this vaccine allocation program, a total amount of 694.236 vaccines is scheduled to be available for Rohingyas over three batches. The fraction needed for the Nayapara Camp B block is estimated based on the total population of Rohingyas and the population of study. Table 4.6 shows an overview of the default amount of vaccines.

Table 4.6: Formalization of vaccine scarcity

	Batch 1	**Batch 2**	**Batch 3**	**Total**
Delivery day	Day 1	Day 30	Day 60	90 Days
Cum vaccine coverage	15%	47%	80%	80%
Expected vaccines Rohingyas (*total camp, 861,545 people*)	129.698	272.070	292.468	694.236
Expected vaccines Rohingyas (*Nayapara B, ~950 people*):	143	300	322	766
Expected vaccines Host Community (275 *people*)	41	86	93	221

For formalizing vaccine allocation strategies, three main factors are used to create and shape the allocation strategy: age, a transmission profile and a population (see table 4.7). Through ages-based profiles, prioritization of different age-groups is formalized. Through a transmission profile, it is possible to prioritize groups with the highest chance of transmitting COVID-19 to another person. With differences between two subpopulations, it is studied what the effect is of excluding the Rohingya refugees from the COVID-19 vaccination program.

Table 4.7: Formalization of vaccine prioritization groups, defined by age, transmission profile or population

Age-group	**Transmission profile**	**Population**
Children	Low risk of transmission	Rohingyas
Young adults	High risk of transmission	Rohingyas & Bangladeshi
Older adults	High risk of transmission	Rohingyas & Bangladeshi
Elderly	Low risk of transmission	Rohingyas & Bangladeshi

4.2.7 Concept IV: Conceptualization of a COVID-19 transmission model

As a result of interactions in the refugee camp, COVID-19 infections happen inside the camp. These COVID-19 infections are conceptualized trough an transmission model, of which an existing epidemic model was introduced in section 3.2. Based on the general structure of this model, a conceptualized mechanism of COVID-19 transmissions between individuals which is used for this research is explained here, for which a separate concept can be found in section D.1.4.

As an input for this transmission model, both the interactions between individuals and demography-based characteristics are important factors. Demographic differences between agents differ from an agent's sub-population (i.e.Rohingya or Bangladeshi) and age (i.e. children, young adults, old adults and elderly). Here, it is important not to confuse the three age-groups related to activity schedules as introduced in section 4.2.2: four age-groups are studies for COVID-19 transmissions, as differentiating over four groups gives better insights in the age-based vaccine strategies. For example, the chance of developing an symptomatic infection from COVID-19 is significantly different ranging over these age-groups Davies et al. [2020]. Regarding differences between sub-populations, a clear difference between Rohingyas and Bangladeshi exists regarding the chance of dying from COVID-19: case facility rates for Rohingyas against Bangladeshi is almost twice as high [Hub, 2021].

Secondly, for different agents it is determined whether they are vaccinated or not. This determination depends on the vaccination strategy, and means a vaccinated agent is protected. Here, for simplicity, it is assumed agents are protected immediately after being vaccinated, rather than growing immunity over a time span of 7 days [Garcia-Beltran et al., 2021]. For example, a vaccination strategy implies all elderly are prioritized for vaccination. In case sufficient vaccines for all elderly are available, all elderly will be protected for a COVID-19 infection. The concept of vaccine strategies is discussed more briefly in section 4.2.1.

Based on the two inputs, non-vaccinated, susceptible individuals can be exposed (E) to other agents who are infectious, with a chance of getting infected. Here, agents can become asymptomatic (A) or symptomatic (I) or asymptomatic and being vaccinated (Av). For this last stage, agents are vaccinated but still infectious to others. This has been studied, as current research on COVID-19 vaccines do not clearly show non-vaccinated individuals can be infected by vaccinated individuals Peiris and Leung [2020b]. Agents with symptomatic infections are assumed to know they have COVID-19, making them decide to isolate themselves from other agents. However, as concluded in chapter 2, compliance to measures (e.g. staying at home) is low in poor areas, such as refugee camps. Therefore, a factor of compliance is determined for individuals, which makes them comply to isolate or not. For asymptomatic infections, it is assumed agents have no risk of dying (D) from COVID-19. Therefore, only symptomatic agents can die with a certain chance; others recover (R).

4.2.8 Concept IV: Formalization of a COVID-19 transmission model

To formalize the COVID-19 transmission concept, this research follows some of the or simplified equations as proposed by Foy et al. [2021]. The equations aggregate to a transmission model, using a total population (N) with susceptible individuals with an age group i and a sub-population j. Following the transmission stages of a susceptible population S_{ij}, the transmission model progress as follows:

$$N = S + E + I + A + Av + V + R - D \tag{4.2}$$

Equations which are used for each of these stages can be found in appendix D.2.1. These equations are based on the following model parameters. β_1 describes the force of infection. This parameter controls the rate of the spread (i.e. the probability of a transmission between susceptible and infectious individuals). In this research, different forces of infection are considered for different age-groups and sub-population, based on estimations of Davies et al. [2020] (see appendix D.2.2). σ, ω and γ are rates used to progress between different disease transmission stages, and are derived from generally available data on incubation times, post-isolation recovery (i.e. for symptomatic infections) time and recovery times in general (for asymptomatic infections). p describes the probability of becoming symptomatic after an exposure to COVID-19. To determine p, which is also age-based specific, data is used from a research by Mannan et al. [2021], showing the ratio of asymptomatic versus symptomatic individuals in Bangladesh. Here, Rohingyas face far less symptomatic infections from COVID-19, as Lopez-Pena et al. [2020] concludes only 24% of the Rohingya population shows symptoms (such as fever, dry coughs or fatigue). δ is used as a death-rate, which is based on data from Hub [2021] on both Rohingyas and host communities. Based on the vaccine allocation strategy, M number of vaccines are allocated to individuals, with an effectiveness of vaccines of ϵ. Lastly, β_2 is set to 1 if vaccinated individuals are still infectious to others. All parameters and sources to formalize these parameters with relevant data are shown in table 4.8.

Table 4.8: Average formalized transmission model parameters for Rohingya & Bangladeshi population

Parameter	Meaning	Rohingya	Bangladeshi	Unit	Source
β_1	Infection force	age-based	age-based	rate	Davies et al. [2020]
$1/\sigma$	Incubation time	5.2	5.2	days	Lauer et al. [2020]
$1/\omega$	Post-isolation rec. time	16.4	16.4	days	Bi et al. [2020]
$1/\gamma$	Recovery time	6	6	days	Bi et al. [2020]
p	Rate of symptomatic inf.	age-based	age-based	rate	Mannan et al. [2021]
δ	Death-rate	0.022	0.011	rate	Hub [2021]
M	Available vaccine doses	Variable	Variable	doses	-
ϵ	Vaccine effectiveness	Variable	Variable	rate	-
β_2	Infectious if vaccinated	[1,0]	[1,0]	binary	-

4.3 SYSTEM INTEGRATION

Systems differ from unorganised heaps, which also have multiple components, by the fact that the elements are interdependent and interact [Van Dam et al., 2012, p.17]. These inter dependencies and interactions between the sub-concepts are conceptualized and formalized to an integrated system. To do so, the sub-concept's general links are explained and a general structure of the integrated concept is presented. To make this concept operable for an ABM, it has been formalized in line with the case study. In this section, some sub-concepts are presented as a simplified version. Appendix D presents all these more detailed.

4.3.1 Conceptualization of integrated sub-concepts

A concept of the integrated system can be found in figure 4.4, created through a flowchart structure. Flowcharts are diagrammatic tools for representing processes or flows in a system. The integrated system consists of the four main sub-concepts from section 4.2. Together, the integrated system consists of four parts:

1. **Sub-concept 1:** Interactions in an open-system refugee camp
2. **Sub-concept 2:** Camp openness
3. **Sub-concept 3:** COVID-19 vaccine allocation strategies
4. **Sub-concept 4:** A COVID-19 transmission model

Daily interactions in an open system refugee camp and COVID-19 transmissions (concept 1 & 4), are linked through a positive feedback mechanism. This mechanism works as follows. A day starts when refugee households wake up. At that moment, these households determine a shared daily schedule and their health condition: in case this

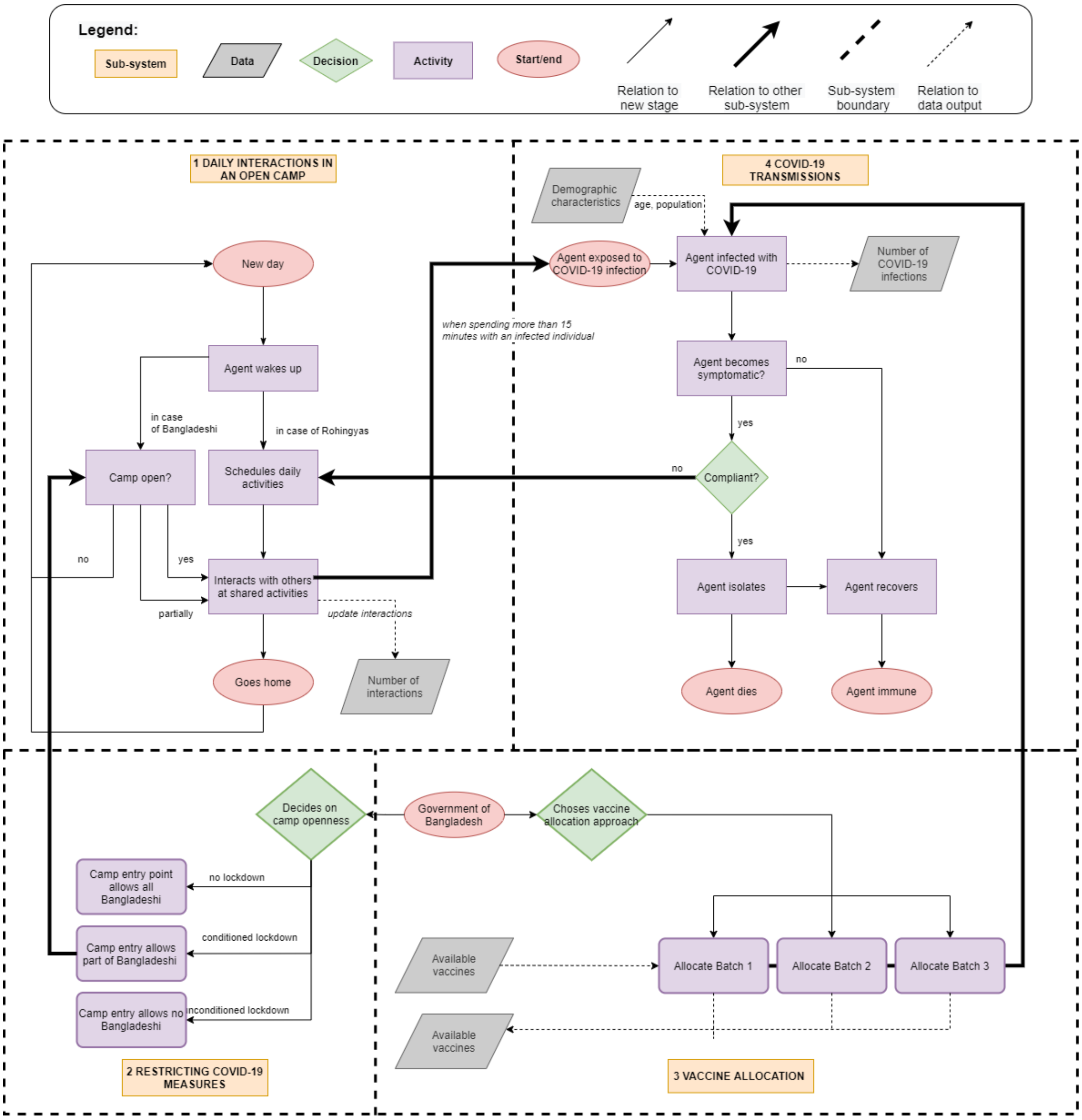


Figure 4.4: Integrated concept of system sub-concepts

health condition is good (i.e. nobody in the household has COVID-19), individual agents leave the household to execute activities where they interact with others. For example, children go to school, and the elderly go pray in a mosque. These interactions serve as a first link to cause COVID-19 transmissions: when individuals are exposed to another infected individual, they can become infected. Here, demographic characteristics such as age and a health-profile influence the development of a symptomatic or asymptomatic infection.

The second link, going back from the transmission model to daily interactions, relates to individual compliance isolation when a household is infected. It is assumed individuals know about themselves to be infected with COVID-19 in case of a symptomatic infection. When an individual decision not to comply and not to go into isolation, they follow their daily activity schedules. Here, the second link exists, going back from the transmission component to the daily interaction components, but here a higher share infectious individuals interact with susceptible individuals. This is an enforcing feedback loop, as more infectious individuals will interact with others in case of low levels of compliance, with more COVID-19 infections as a result.

Furthermore, two links go from the response coordinator's perspective to influence the interactions among individuals inside the camp with restricting measures (concept 2) and to influence the number of infections with vaccine allocation strategies (concept 3). The third link is a one-way influencing relation from the camp openness component, affecting the number of host community people entering the camp. The government regulates the entry points of the camp site, on three levels of strictness. These levels of strictness are based on the number of COVID-19 cases inside the camp: if cases rise, the government decides to introduce a lockdown measure, isolating the camp and keeping out the hosting community. The effect of this is less interactions happening inside the camp. As interactions serve as a measure for gaining livelihoods, this means the life conditions of the people inside the camps decrease.

The fourth link describes the mechanism of vaccine allocation on the COVID-19 transmission process. When individuals are vaccinated for COVID-19, their infectiousness decreases. Different vaccine allocation approaches can be chosen, based on demographic characteristics of individuals and on different levels of COVID-19 infections. Based on the approach, individuals are vaccinated, meaning these individuals are excluded from the transmission process. In that case, less infections will happen inside the camp, lowering the chance of the government closing down the camp through lockdowns measures.

4.3.2 Formalization of integrated environment

As a last step for translating the integrated system into a model, it is formalized. With this, the aim is to translate and formalize the integrated concept from previous section, by explicitly defining and operationalizing each concept of analysis. In this way, a fully integrated and context-specific conceptual model is created in line with both the theoretical basis of this study and the practical context of the case study. This last step of formalization of the integrated model adds value to this research, as it lowers the level of ambiguity of the model and creates more context dependency related to the domain of study [Van Dam et al., 2012]. More practically, this last step of formalizing allows to set a basis for a conceptual model of the Nayapara refugee camp case study and the model concept which fits the context of this.

A high-over, UML-based formalization of this formalized model is depicted in figure 5.1. This formalized concept contains the ABM-structured core elements which have been translated to construct a model of analysis (further discussed in chapter 5). It shows several physical and non-physical elements (*agents* and *objects*) of the model, their inner states and actions and the environment in which these elements exist. For example, individuals from the figure reflect both Rohingya refugees and Bangladeshi. Individuals from both groups have overlapping properties, such as age, a daily destination and have COVID-19-specific characteristics. Based on their properties (such as their destination), these individuals carry out certain actions (such as executing an destination-based activity). A more complete overview of this integrated formalized concept is discussed in D.2.5.

4.4 MODEL KEY PERFORMANCE INDICATORS

To study the behavior of the system from previous sections, two main KPIs have been chosen: the first KPI measures the *number of COVID-19 infections* in the open system refugee camp environment. The second KPI measures the *number of interactions* among refugees and with host communities. By conducting experiments with the model, it is analyzed how both of these KPIs develop over time and be influenced by different vaccine allocation strategies. Here, it is the aim to explore how these strategies influence the dynamics between creating economic freedom (measured in *interactions*) whilst keeping health secure (measured in *COVID-19 infections*). By doing so, the earlier named trade-off between both these KPIs is researched.

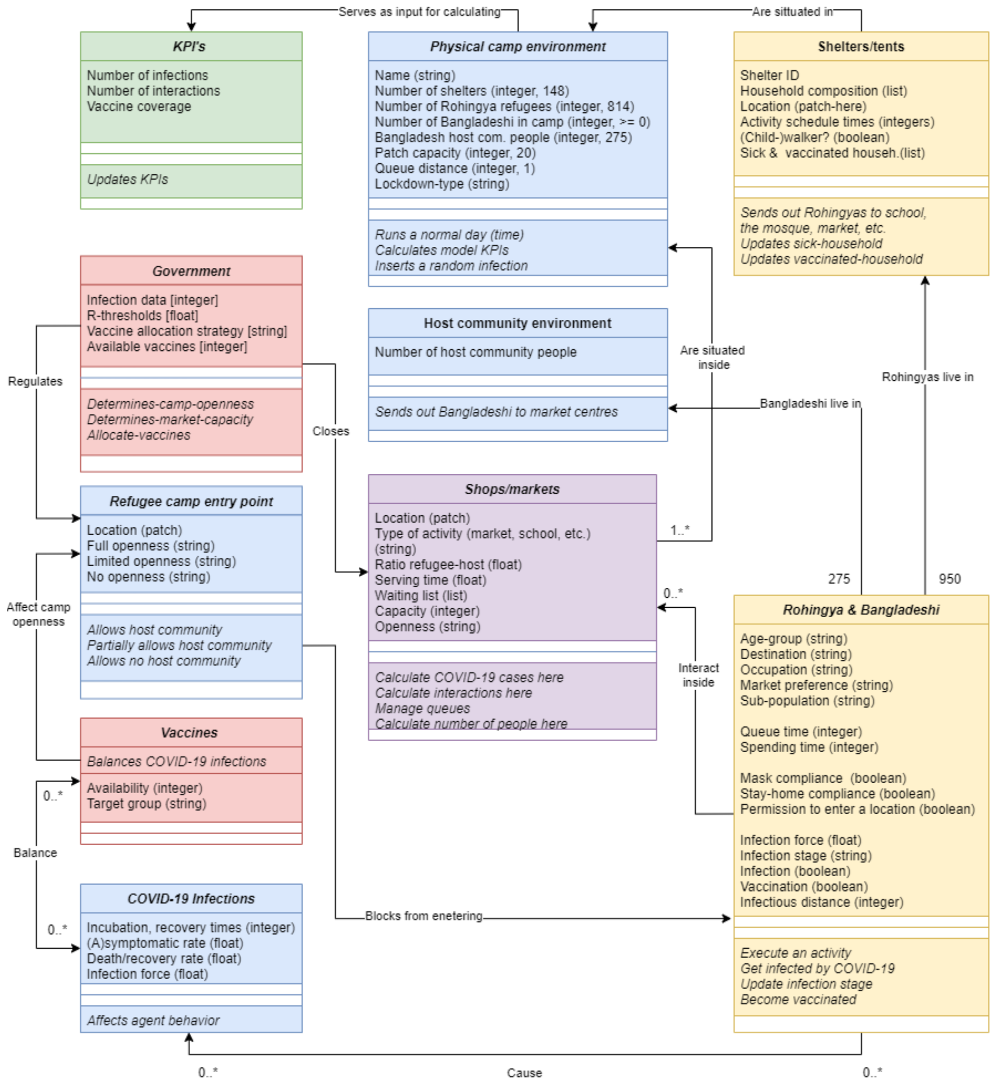


Figure 4.5: UML-based formalization of the integrated concept

4.4.1 KPI 1 Infections

COVID-19 infections are studied by measuring the number of individuals who are infected by COVID-19. Getting infected is caused by a susceptible individuals, who is exposed to an infectious person and gets infected after a certain incubation time. From the moment an individual reaches the stage of being symptomatic or asymptomatic, a COVID-19 infection is measured. By measuring COVID-19 infections, a KPI is defined which measures the potential balancing mechanism for allowing more interactive freedom (measured with *interactions*, see section 4.4.2). Being infected with COVID-19 is assumed to be a result of not being immune for COVID-19, which applies to non-vaccinated individuals or recovered individuals who have become re-infectious. Therefore, this KPI allows for studying the effect of different vaccine allocation strategies, as these reduce the group of infectious people and therefore the potential spread of COVID-19 through the refugee camp.

COVID-19 infections are a common measure for comparing vaccine allocation strategies in other literature. For example, Foy et al. [2021] and Matrajt et al. [2020] measure the effect of different strategies on the number of infections. Tuite et al. [2021] measures COVID-19 infections as the adverted relative benefiting effect of vaccinating, relative to not vaccinating. Examples of other KPIs which are used in literature relating to the impact of vaccines and COVID-19 are metrics such as deaths or mortality rates, morbidity rates or pressure on hospitality and availability of healthcare workers/facilities (e.g.

[Matrajt et al., 2020]). Also, the KPI of COVID-19 infections can be further explicated by differentiating between asymptomatic and symptomatic infections (or for symptomatic infections even further differentiated over normal, severe and critical infections, as by Shim [2021]).

However, as the main aim of this study is to research the trade-off between health and economic values, it is chosen not to differentiate over many KPIs which reflect only health-based metrics. Measuring COVID-19 infections as a first KPI is assumed to be a good metric for determining effective allocation strategies, as it sufficiently reflects health-based factors which can be set as a trade-off for interactive freedom. Lastly, for measuring COVID-19 infections, a last assumption which is made relates to the complete knowledge on the number of infections. This assumption implies the government has accurate information on COVID-19 cases which are registered in the camp. This assumption is made for simplicity, and is reflected upon in chapter 9.

4.4.2 KPI 2 Interactions

Interactions are studied by measuring the number of visits by individuals at mixed or shared facilities and locations. An individual is measured to 'interact' with others by deciding to visit one of the public places, such as a mosque, market or a school. One could argue the definition of a real interaction, but it is assumed visiting a public spot in the refugee camp environment is in favour of an individuals livelihood. Therefore, a visitation to one of these livelihood-generating activity destinations is measured as an interaction. Preferably, the number of interactions by both refugees and host communities is as high as possible for livelihood-generating activities.

This KPI is not selected randomly. Other studies mention interactions as a good measure for livelihood-generation in refugee camp contexts. For example, [Porter et al., 2008, p.1] mentions *"The reported experiences of camp residents and of the people with whom they **interact** in their efforts to make a living (...) illustrate the complex interplay between personal networks, livelihoods and broader relations between refugee and host population"*. Alix-Garcia et al. [2018] uses interactions as a measure for economic activity between refugees and host communities in Kenya. Agblorti and Awusabo-Asare [2011] names interactions between refugees and host communities as a factor for peaceful coexistence and economic development. Werker [2007] mentions interactions as an important source of market outcomes in refugee camp economies, such as income. Many other studies use interactions as a measure for economic activity and/or livelihood generation. These are not discussed here, but are for example Montclos and Kagwanja [2000], Jacobsen [2002] or Oka [2011].

To formalize interaction in this study, a formalization of interactions by Alix-Garcia et al. [2018] is used. They define an interaction as the inflow of a refugee/individual from a host community into a certain area. In this research, this is expressed as the visitation of one individual to a place which is not their home/shelter.

4.5 VACCINE ALLOCATION STRATEGIES

The effects of five vaccine allocation strategies are measured an compared. These strategies are set-up through the demography-based approach and are formulated by weighing two criteria:

- The strategy is feasible to implement in a refugee camp context
- The strategy is likely to be considered by a decision-maker in the Rohingya camp context

For the first criteria, it is assumed the feasibility of implementing a vaccine allocation strategy reduces if differentiating over too many different prioritization groups. This is due to the fact that in refugee camps, registration and regulation is relatively complex, given the scale of the refugee camp and the level of emergency the people are in [Oh, 2017]. Differentiating over too many prioritization groups will be a complex, administrative task which is not desirable or feasible for implementation. This challenge was addressed in vaccination programs prior to COVID-19, by Jalloh et al. [2019]. To account for this administrative barrier, strategies are defined by four age-groups, two types of transmission profiles or their population. For the second criteria, it is researched how likely the initial vaccine allocation program in Bangladesh can be modified to a new strategy. Namely, an initial allocation program exists (see Government of Bangladesh et al. [2021]) but has no academic or informed-based support. It is accounted for the fact a flexible change in this program is more desirable than proposing a highly complex and new strategy.

Table 4.9 summarizes the formalized concepts of each of the strategies as discussed in next sections. To formalize these strategies, data is used from table 4.6.

Table 4.9: Vaccine allocation strategies as explored in this research

Allocation strategy:	Academic approach:	Prioritization order:
1. Elderly first	Age-based	Elderly, old adults, young adults, children
2. Children first	Age-based	Children, young adults, old adults, elderly
3. Equalizing	Geography-based	Equal prioritization
4. Bangladesh only	Geography-based	See elderly first, only host communities
5. Transmission group	Transmission-based	Young adults, old adults, children, elderly

4.5.1 Strategy 1: Elderly first vaccine allocation strategy

The EF strategy prioritizes elderly people. This strategy is adapted from the current Bangladesh NDVP, which defines the elderly as people over 40 years of age in context of the Rohingyas. In this research, elderly are categorized by their age of 60 or older. Following age-groups through this strategy are old adults (40-60 years), young adults (18-40 years) and children under 18 years. Based on the expected availability of vaccines and the expected number of batches, the allocation mechanism for this strategy is shown in figure 4.6. Concepts for other strategies can be found in appendix D.4.

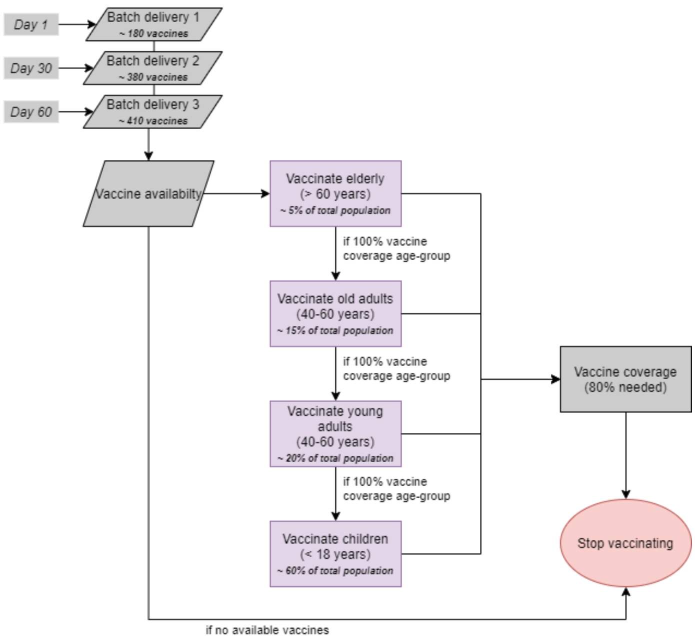


Figure 4.6: A formalized concept for the vaccine allocation mechanism for the EF strategy

4.5.2 Strategy 2: Children first vaccine allocation strategy

The Children first strategy (CF strategy) prioritizes children. This strategy is set-up to explore if vaccinating children first is an effective strategy, as children are predominantly representative in the Rohingya population and are an active age-group. Although the force of transmission from child-to-child and from child-to-adult is relatively low compared to other age-groups, their activeness and large size make children a potential risk for transmission to older people. When transmitted from child to their parents, these can then further transmit the infection to others. To prevent this, vaccinating children can be an effective strategy, which is derived from [Duijzer et al., 2018]. A successful vaccination campaign which prioritzed children prior to the outbreak of COVID-19, was during the diphtheria outbreak in the Rohingya camps, in 2017. This success was due to the fact that children have highest contact rates with other children, increasing the chance of transmission. This was mostly compensated by vaccinating children below 15 first [Rahman and Islam, 2019].

4.5.3 Strategy 3: Equalizing vaccine allocation strategy

The Equalizing strategy (EQ strategy) does prioritize, as every individual has equal access to vaccines. This strategy is a derivative of *region-based* vaccine allocation, which means vaccines are allocated evenly over predefined groups within a population where infections are high. These groups can be a household or a community, which is applicable to a refugee camp context [Duijzer et al., 2018]. In practice, this strategy would implicate a certain proportion of each household or community gets vaccinated, lowering the chance of infections here [Ball and Lyne, 2002]. In this research, these households are conceptualised as shelters, and for each of these shelters vaccines are allocated evenly among its inhabitants. This strategy is studied for two reasons: firstly, it allows for exploring whether an even proportion of vaccinated individuals in each shelter is an effective way of reducing infections. Secondly, the EQ strategy is relatively easy to implement, due to its simplicity for not differentiating over many sub-groups within a population [Duijzer et al., 2018]. Therefore, the strategy is judged to have a relative low administrative nature in combination with significant effectiveness for reducing infections (see chapter 2.3.3). This can be valuable in a refugee camp context, as response coordinators need to deal with low administrative possibilities.

4.5.4 Strategy 4: Bangladesh only vaccine allocation strategy

The BO strategy excludes the Rohingya population from the vaccine program (i.e.only host communities are vaccinated). This strategy can be linked to vaccine allocation problems with multiple interests: in literature, this applies to a context of multiple decision-makers who have to decide on vaccine allocation separately but with overlapping interests [Duijzer et al., 2018]. For example, governments from two bordering countries with people crossing these borders where one country has access to vaccines and the other does not can decide to balance their vaccine stockpiles. If not shared, the country without vaccines can be a potential source of infections, risking spillovers from outside. In this research, this principle is translated to the Rohingya population as one 'country', and the host community at the other. Although one decision-maker formally decided on the vaccine program in Bangladesh (i.e.the national government), there are some indications the Rohingyas will not or very late be included in the vaccination program. For example, UNHCR in an early stage expressed its worries if and when the Rohingyas will (sufficiently) be included in the vaccine programmes in practice UNHCR [2021b]. This is now backed by a report from the *Human Rights Initiative*, which stresses none of the Rohingyas has received a vaccine in June 2021, whereas vaccination programmes for the local population started in April 2021 [Global COVID-19 Consortium, 2021]. This implicates, although the Rohingyas are theoretically included in the vaccination program in Bangladesh, it is questionable they will be in practice as well. Linking to the example from the two countries with unequal access to vaccines, this strategy explores the effect of excluding Rohingyas from the vaccine program, which from an academic viewpoint is not desirable, but in context of the Rohingyas is not unimaginable.

4.5.5 Strategy 5: Transmission group vaccine allocation strategy

The Transmission group strategy (TG strategy) prioritizes individuals with a high risk of transmitting COVID-19 to others. In this research, active groups are mainly adults, followed by children and elderly. Adults go out of their shelters more than others, and therefore have the most livelihood-generating activeness in the camp. This means, individuals with high risk transmitting profiles might be a threat from a health-based approach, they also represent most economic value. In a refugee camp context with a relative small group of elderly (who face most health-related risks from COVID-19), this strategy is used to explore if vaccinating high-risk transmission groups first can create more economic freedom whilst reducing infections. Here, health-related factors are not put aside for weighing the effectiveness of the strategy (as elderly are vaccinated late), as some studies point out the prioritization of transmitting groups will also benefit the vulnerable and elderly (e.g.Yamin and Gavious [2013]).

4.6 MODEL ASSUMPTIONS & SIMPLIFICATIONS

Every system description must contain an explicit definition of what is in the system and what is outside it [Van Dam et al., 2012, p.18]. The explicit definitions and conceptual elements of the system of study as discussed in this chapter are based on several assumptions and simplifications. The core assumptions and simplifications in this research are summed up below, as they give a more in-depth understanding of the model. This list with a more complete explanation can be found in appendix D.3.

4.7 CONCLUSION

In this chapter, a formalized concept of an open-system refugee camp is created. In this system, four sub-concepts are integrated: (1) the interactions between Rohingyas themselves and with the host community in this open-system, (2) COVID-19 measures, (3) vaccine allocation and (4) a COVID-19 transmission model. These sub-concepts were linked and integrated, to study the effect of five vaccine allocation strategies which were also conceptualized: an (1) Elderly first, Children first, Equalizing, Bangladesh only and Transmission group strategy. These strategies prioritize different sub-groups within the Rohingya and Bangladesh population, based on their age, transmission profile or sub-population. The main objective this chapter has covered is to set a conceptual basis for creating a model which can be analysed. To do so, several several assumptions were made to capture these concepts into a model which is feasible for analysis, which were discussed as well. In chapter 5, this formalized concept is translated to a model.

5 MODEL FORMALISATION & IMPLEMENTATION

Chapter 5 gives an answer to sub-question 4 of this research: *How can this formalised concept be integrated with an existing agent-based model on COVID-19 infections in refugee camp settlements?* To create a model from the formalized concept which was introduced in chapter 4, this chapter presents how a model has been constructed. To do so, the modelling software is introduced in section 5.1. Then, a description of the model is presented in section 5.2. Section 5.3 discusses techniques which are applied to verify (parts of) the model. Lastly, section 5.4 concludes.

5.1 MODELLING SOFTWARE

The model has been developed in the ABM modeling language *Netlogo*, developed by Uri Wilensky. Netlogo is used as it offers a practical simulating language for agent-based models an approach to simulation in which the system under investigation is represented, as it is a popular tool in the academic world of agent-based modeling. It makes use of an interactive and visualized interface, and is a useful tool for the development of ABM models [Van Dam et al., 2012]. The created model which is used for this research can be found here:

https://github.com/felixwilbrink/thesis.git

5.2 MODEL DESCRIPTION

5.2.1 Model Interface

The model interface displays the open system refugee camp environment, in context of the case study environment. In the interface, the Rohingya Nayapara RC environment is shown with shelters, hosting Rohingya households, and the host community site with local Bangladeshi. Both populations interact with each other according to their individual schedules, at shared, in-camp facilities and the vicinity market. In this way, the model is a simplified representation of the demarcated area which was shown previously, in figure 3.1.

The number of interactions which take place in the camp environment is tracked and visualized on the right hand side. In the first and third graph on the right, current and cumulative interactions are tracked. From these interactions, COVID-19 infections can be a result. When susceptible individuals meet an infectious person, they can become infected. From that moment, the disease progression of sick individuals is updated and visualized in the second and fourth model plots on the right.

Both infections and interactions are influenced by different model parameters, which can be adjusted on the left side. These parameters (see 5.2.3) define both restricting COVID-19 measures and vaccine allocation strategies, influencing and influenced by the individual behavior of agents inside the model. For example, camp openness is determined based on the weekly growth of infections, and limits the number of entrances at the camp and the capacity of the big market. Then, vaccines have a positive effect, as less COVID-19 infections are expected and the camp can open its borders for longer.

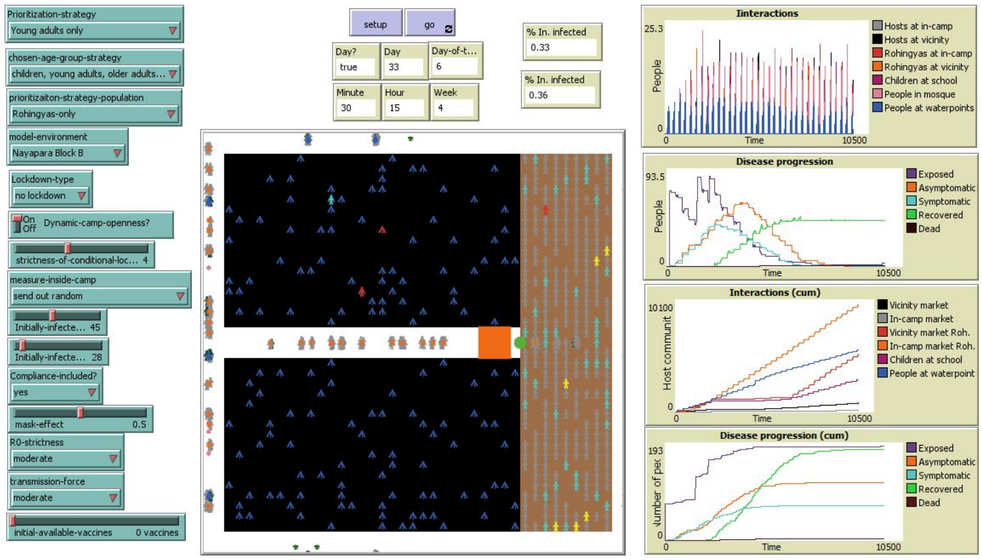


Figure 5.1: Model Interface

5.2.2 Model structure

To create this model, a model narrative and pseudo-code have been used. With the model narrative, the behavior of the agents inside the models is captured into a story, which describes which agents do what, with whom and when they do it [Van Dam et al., 2012]. With the pseudo code, the last step is set for translating the model narrative to *Netlogo* code, which is the modelling software used for this research. In this model, the four main concepts as integrated in chapter 4 are captured. These concepts are formulated in a sequential structure, which is the modeling structure of *Netlogo*. This means, the code which has been used to reflect these concepts describes how the model behaves for each step in time. In each step, the model runs over lines of code which are read in sequential order, where information from previous lines is used as input. In this way, each step in time is influences by changes in the previous step. For example, a refugee *first* assesses her health status (i.e.the refugee assesses whether she is healthy or infected), *then* decides, based on this status, if she is compliant to behave according to the rules which correspond to this health status (e.g. decide to stay-at-home when infected). An example of risking COVID-19 is presented below. Two other examples can be found in appendix E.1.

Example Model Narrative: risking COVID-19 at shared facilities
When individual agents leave their shelter (Rohingyas) or enter the camp (host communities), each agent carries a health-status: susceptible, exposed, (a)symptomatic, recovered or vaccinated. This health status determines whether an agents forms a risk for others (when they are (a)symptomatic), or can get infected by someone who is infected (when susceptible or recovered but re-infectious). A susceptible individual risks an infection when an infectious person is in a 1.5 meter distance, and the longer someone stays in that distance, the higher chance will be this person gets infected. After 15 minutes of spending time within 1.5 meter distance, the healthy person gets infected at all times. Up to that time, a growing risk to be infected depends on the following demographic factors: the *force of infection*, the *age-group* and the *population* of the healthy individual. Also, the force of infection depends on whether the healthy person wears a face-mask for further protection.

In appendix E.1, the complete model narrative and pseudo code can be found.

Algorithm 5.1: Risking to get infected with COVID-19 at a shared location

Input: Susceptible or re-infectious individual that is not vaccinated
Output: Health-status: susceptible → exposed

```
1 while At least 1 infectious person in-radius 1.5 meter: do
2   Set time-with-infectious-person + 5 time-with-infectious-person < 15
      minutes set a-chance-to-get infected random-float (1)
3   let transmission-force [an age & population-dependent rate]
      a-chance-to-get-infected < transmission-force x
      time-with-infectious-personbecome exposed to COVID-19 stay healthy
```

5.2.3 Model parameters

The model structure is based on several model parameters, of which some cannot be formalized with high levels of certainty. The exploratory nature of this study implies that the parameters which describe the sub-concepts and their integration in the model can not be expressed by a single value. Other parameters vary as these represent policies which are tested in the model, for which different parameter values can be used. The most uncertain parameters in the model are presented in table 5.1.

Table 5.1: Parametrisation of the model

Sub-concept	Parameter	Value range	Units
Open-system refugee camp	Rohingya pop.	140-145	# Shelters
	Host community pop.	250-300	# People
	# in-camp facilities	80-90	$ Facilities
	# in-camp shops	14-17	# Shops
	Spending time facilities	5 min - 2,5 h	Minutes/hours
	Frequency of visiting facilities	1-3	# Visits/household
COVID-19 measures	Lockdown	No/cond./uncond.	Lockdown type
	Camp capacity	0-100%	# of people
	Facility capacity	0-100%	# of people
	Mask compliance	0-100%	Compliant # households/ total # households
	Stay-at-home compliance	0-100%	Compliant # households/ total # households
	Ro threshold	0.85-1.5	Infections week n/ infections week (n-1)
Vaccine allocation	Numbers of vaccines	60-140%	Available vaccines
	Numbers of batches	3-5	Deliveries
	Batch delivery day	2-3	once per x months
	Allocation strategy	1-5	See table 4.9
COVID-19 transmission	Mask-effect	0.4-0.6	rate
	Force of infection	0.05-0.82	age-specific rate
	Re-infection time	100-1440	days
	Symptomatic rate	0.7-0.95	population-specific rate
	Death rate	0.011-0.022	population-specific rate
	Incubation time	4-6	days
	Recovery time	4-7	days

5.2.4 Running the model

Running the model, a time period of 90 days is studied. When setting up and running, each time step consists of 5 minutes representing the real world. This combination of low granularity and long time frame is chosen, as then the process of infections can be studied on one hand, and the effect of different batches of vaccines being allocated to the population on the other hand. Namely, COVID-19 infections are a result of close interaction among agents and the chance of getting infected increases in short time periods of only 15 minutes. The arrival of new vaccines is with intervals of months, which is the reason a 90 day time frame is chosen. In 90 days, or 3 months, the arrival of three different batches of vaccines can be studied and its effect over time can be measured. In this way, the model considers the fact of vaccine scarcity.

When running the model, sequential steps are carried out for each moment in time. Here, both global variables and the properties of individual agents need to be tracked. This means, in each step model parameters and agent-specific properties are updated and set as new input for a next step carried out in the model. This makes the code computationally intensive to run, in combination with the low resolution and long running-time of the model. To make the model less computational, some adjustments are made to the model:

- Time runs, but agents are only directed to carry out activities during the day (8am-6pm). In this way, running during the night becomes less computational as agent-specific loops are set off.
- Agents in the model are represented by shelter-agents, which house their household members. Only if one of its household members becomes active (e.g. visiting the market), a new agents is hatched from the household and is active until returning back home. Then, only the agent's properties are added to the household, and the individual agents "*dies*". In this way, the number of agents in the model remains relatively low compared to the population size which is studied.

5.3 MODEL VERIFICATION

Verification checks that all relevant entities and relationships from the conceptual model have been translated into the computational model correctly [Van Dam et al., 2012, p.98]. During the process of constructing the model, several iterative rounds of verification techniques were applied. Verification of mechanisms, processes and structures in the model is an essential part of modelling, as it raises its credibility and correct representation of the concepts which have been defined previously [Thacker et al., 2004]. Relating to this research, verifying the modeling concepts is done to make sure the four sub-concepts are implemented into a model as intended. By doing so, a well-verified model raises the decision-making power of the model.

To verify different (sub-)processes in the model, four verification techniques were used, adapted from Van Dam et al. [2012]: (1) recording and tracking agent behavior, (2) single-agent testing, (3) interaction testing a minimal model and (4) multi-agent testing. An example of these techniques and how these are applied can be found in appendix E.3. This overview is not complete, but creates an idea of how the model has been verified; more verification checks were carried out during the process of modelling, but these are not mentioned as these checks were relatively small and therefore considered to be part of the modeling process.

5.4 CONCLUSION

This chapter presented the formalization and implementation of the conceptual model into a model which was used for analysis. To do so, *Netlogo* was used as a modeling software for ABM. Through the interactive model interface, a model is constructed with the use of a model narrative and the development of pseudo code. This pseudo code is translated through several model parameters, which define the four integrated sub-concepts. To check whether these concepts were modeled as intended, several verification techniques were applied.

In chapter 6, experiments are introduced for this model.

6 MODEL EXPERIMENTS

Chapter 6 presents the experimental setup which has been used to analyse the system of study. Performing different experiments with the model allows to study the emergent patterns and behavior which result from it [Van Dam et al., 2012]. Therefore, this chapter sets the basis for answering sub-question 5 in this research: *How can the dynamics between refugee-host interactions, the spread of COVID-19 and vaccine allocation strategies be explained with an agent-based model?* With experiments it is aimed to study these dynamics, in relation to different policies and with the model. To do so, section 6.1 presents the experimental design. Section 6.2 then discusses the execution of experiments. Lastly, a conclusion is drawn from this chapter in section 6.3.

6.1 EXPERIMENTAL DESIGN

The goal of the experiments is to study the dynamics between refugee-host interactions, the spread of COVID-19 and vaccine allocation strategies. To do so, a two-level and three-level fractional factorial design is applied, derived from Wu and Hamada [2011]. Two or three-level designs are a common tool of experimentation for models with over approximately seven variables, and are a less time-consuming way of experimenting with a model [Wu and Hamada, 2011].

6.1.1 Hypothesis-driven experiments

Through this experimenting design, experiments were defined through a set of two types of hypotheses as derived from Van Dam et al. [2012]: a **type 1** and a **type 2** hypothesis. A type 1 hypothesis can be used to experiment with a model with settings which are expected to be closely linked to a real-world context. In this research, this type of hypothesis is used to get a better understanding on the single effects of different policies and model structures in the model. For example, the single effect of different vaccine allocation strategies are measured using this type of hypothesis. A type 2 hypothesis is more exploratory, as the phenomenon of studies does not clearly match a real-world context. In this research, type 2 hypothesis are used to study model behavior which explores the dynamics between vaccine allocation strategies, infections and refugee-host interactions. Here, no specific hypothesis is formulated, but the exploratory nature of the fifth research question in combination with the insights from type 1 hypotheses are used as a basis for these experiments. In this way, different vaccine allocation strategies can be compared and interpreted by the discovering of *scenario spaces*. In appendix F.4, an overview of these hypotheses can be found.

6.1.2 General experimenting structure

Through the experimental design and for each hypothesis, parameters are selected and varied with based on their expected influence on both KPIs. Three three types of experiments are carried out:

1. A base case experiment
2. Experiments for testing the single effects of limited camp openness and vaccine allocation strategies
3. Experiments on which combinations of limited camp openness and vaccine allocation strategies are applied

The base case model is used for setting a basis for the maximum numbers of infections and interactions if no restricting or benefiting policies are active in the camp environment. Also, insights are gained on the number and types of infections which happen in that case, and how many and what types of interactions cause these infections. In this way, the outcomes following from this base case serve as a benchmark for comparing the effect of different policies later on. For the second type of experiments, the effects of different types of camp openness (influencing interactions) and vaccine allocation strategies (influencing infections) in isolation are measured. In these experiments, the influence of different policy measures can be measured and compared with others: a relative effect of each measure can be concluded and the model structure and outcomes are better understood. The third type of experiments are used to find the trade-offs for infections and interactions, as was aimed in this research. By combining (temporal) restricting measures and applying different vaccine allocation strategies, the dynamics between different (types of) interactions and their following (types of) infections are studied.

6.1.3 Model Experimenting Parameters

To conduct these experiments, variations for different parameters are used. The general model parameters which are used were introduced earlier in table 5.1. Based on the hypothesis-driven experimental design, model parameters were selected based on their expected influence on the main KPIs in this research. The initial settings of these experiments can be found in appendix F.2.

6.2 EXECUTION OF EXPERIMENTS

6.2.1 Temporal boundary for experiments

For each run in all experiments, a temporal boundary is defined for 90 days. This temporal boundary matches the maximum expected time in which the model behavior is and can be studied. As the model of study has a relatively high level of detail (single time steps in the model match 5 minutes of real-world representation), a temporal boundary is defined up to 3 months (or 90 days). Namely, during the modeling creation and the verification of the model, this time frame was found to be right for studying the main KPIs of study. Table F.1 in appendix presents these temporal settings.

6.2.2 Selected number of runs

To generate meaningful insights from the model, model parameters are run over a grid of parameters which are not fully certain. Therefore, each experiment is carried out over a minimum of 100 and maximum of 1000 simulation runs to create reliable results. For experiments with little variations in parameter values 100 runs are performed, where for other experiments 1000 runs are performed. Experiments with little numbers of runs are selected based on their relatively low variations in parameter values, whereas for experiments with higher number of parameter variations more runs are needed to cover a reliable scenario space Van Dam et al. [2012].

6.3 CONCLUSION

Chapter 6 presented a setup for conducting experiments with the model of study. For each experiment, a hypothesis is formulated which serves as a basis for carrying out three types of experiments: a base case experiment, experiments testing policies in isolation and experiments testing policies in combination. In chapter 7, the model results for these experiments are presented.

7 RESULTS OF MODEL EXPERIMENTS

Chapter 7 presents the analysis of data which has followed from the model experiments described in previous chapter. Data analysis is an iterative process of exploring, visualising and interpretation of data [Van Dam et al., 2012]. By doing so, the analysis of these data is done for answering sub-question 5 in this research: *How can the dynamics between refugee-host interactions, the spread of COVID-19 and vaccine allocation strategies be explained with an agent-based model?* This chapter starts by explaining the methodology of analyzing in section 7.1. Then, model results are discussed for a base case model (section 7.2), different types of camp openness (section 7.3) and different vaccine allocations strategies are compared (section 7.4). Based on previous model results, more specific model results are presented for a combination of vaccine allocation strategies and different types of camp openness (section 7.5). Lastly, section 7.6 concludes.

7.1 METHODOLOGY OF ANALYSIS

To interpret the outcomes of each experiment, the main KPIs serve as a main basis for analysis. This analysis is done trough two approaches: by studying *patterns* of data and by studying *outcomes* of data. By studying patterns, insights are gained about the parameter space of the model.

Table 7.1: Two approaches for analysing the outcomes of model experiments

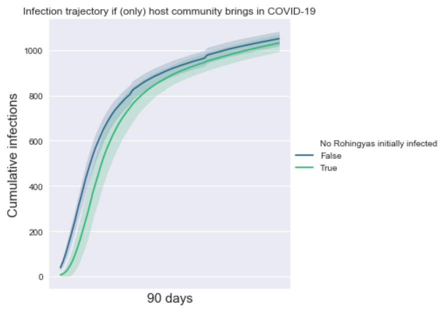
Analysis approach	KPI1: COVID-19 Infections	KPI2: Refugee-host interactions
Pattern analysis	Number of infections over time	Number of interactions over time
Outcome analysis	Cumulative nr. of infections after 3 months	Cumulative nr. of interactions after 3 months

The number of infections is studied by analyzing its pattern, which highlights when infections are most likely to occur at specific moments in time. This pattern gives an indication about the speed in which COVID-19 is spreading among both the Rohingyas and the host community people: different infection curves can develop and can be understood by studying its development. For its final outcome, the cumulative number of infections is measured. With the cumulative number of infections, an indication is created on the total infection coverage of the total population. By studying the pattern of interactions, insights can be gained on how camp openness influences both the current number of interactions and following infections from those interactions. The total number of interactions is used to compare different vaccine allocation strategies and to find a trade-off between these interactions and infections. To interpret both model patterns and outcomes, a base case model is used for a comparison.

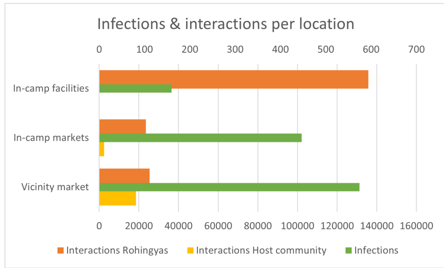
7.2 RESULTS BASE CASE

Model results for the base case experiment are depicted in figure 7.1. In this base case model, no restrictions on interactions were imposed (the camp and its facilities camp remained open at any time) and no vaccines were allocated.

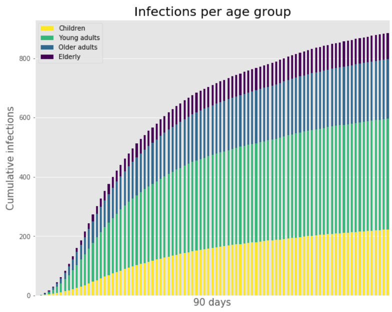
For the development of infections (see figure 7.1a), the model results show the number of cumulative infections will exceed 1.000 individuals, which shows most likely everyone will be infected in 90 days. Here, individuals are assumed to be become re-infectious, which explains the relatively high number of infected people. Most people become



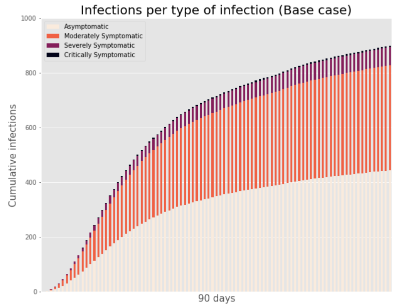
(a) (Effect host community on) infections



(b) Infections per interaction at type of location



(c) Infections per age-group



(d) Infections per type of infection

Figure 7.1: Model results for base case model (500 runs)

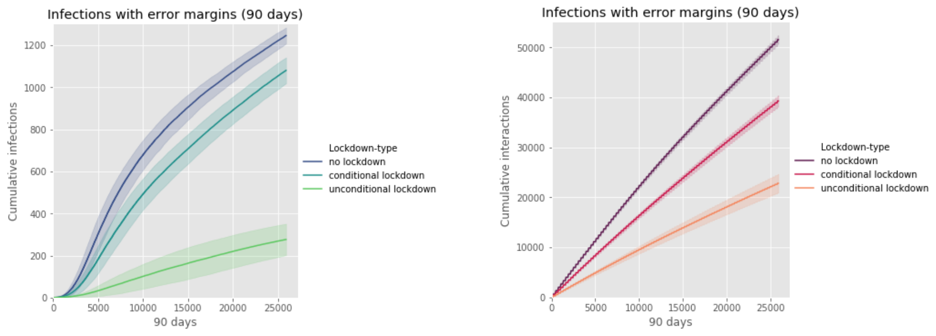
infected in the initial 30 days of the 90 days of study. In this time period, up to 60% of all infections happen which reveals the potential speed in which COVID-19 spreads among the populations. Here, the effect of the influx of host communities shows to be an important factor for triggering an outbreak: a scenario without any Rohingya infected but with infected host communities entering the camp shows to have the same effect on the total number of infections, although with a small delay (figure 7.1a). This can be explained by studying *where* infections happen and among whom: figure 7.1b shows the highest share of infections is caused at the vicinity markets, which is also most frequently visited by host communities. From the interactions here, most infections cover the high-risk transmission age-groups young (47%) and older (26%) adults, which represent only 35% of the population. Children (21%) and elderly (6%) are infected the least (see figure 7.1c). Lastly, figure 7.1d shows the types of infections which occur: most infections are asymptomatic (48%) or moderately symptomatic (44%). The share of severe (7%) and critically symptomatic infections (0.7%) is relatively low but not insignificant.

7.3 TESTING MODEL PARAMETERS FOR CAMP OPENNESS

To better control (different types of) infections, several experiments were carried out for camp openness. Camp openness is varied with from high strictness (i.e.by closing the camp and in-camp facilities completely) to different types of conditional camp openness or openness of specific facilities (such as markets). Camp openness is applied both static and dynamic over 90 days, whereas dynamic camp openness is defined as the opening/closing of the camp and its facilities based on the evaluation of $R0$.

7.3.1 Effect of Static of Camp Openness

Three types of lockdowns and four more specific conditional lockdowns for were implemented. In case of an unconditional lockdown, the camp is fully closed for the host community and the vicinity market is fully closed for refugees. For the a conditional lockdown, movement restricting measures are conditionally raised based on capacity and the level of strictness. The model outcomes for these lockdown-effects are shown in figures 7.2.



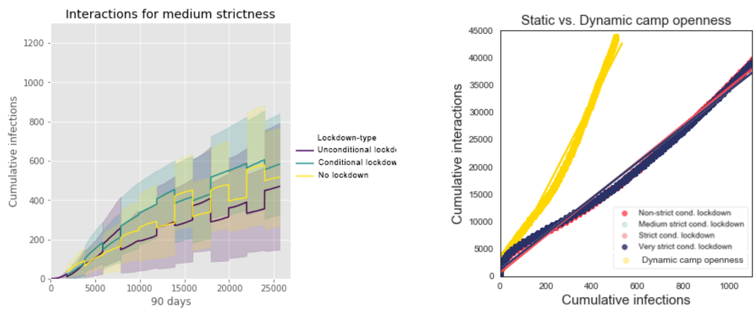
(a) Cumulative interactions **(b)** Cumulative interactions

Figure 7.2: Single effect of 3 types of lockdowns on the number of infections & interactions (300 runs)

From these experiments, two main insights from these results are discussed and used for further analysis of camp openness restrictions. Firstly, limited camp openness for any type has a strong effect on reducing infections. This effect is positive and non-linear: a reduction of interactions causes a *stronger* reduction of infections (as further analysed in appendix G.1.1). Through a static approach, a stricter implementation of camp openness is effective for reducing infections. A second insight relates to the infection trajectory, which shows a more balanced development infection in the initial 30 days. An interesting difference here is the slower spread of infections if children are always free to go to school. This is due to their lower susceptibility compared to other age-groups.

7.3.2 Effect of Dynamic Camp Openness

Static lockdowns are effective for reducing infections, but come with low interactive freedom. To find effective trade-offs between infections and interactions, an experiment was carried out which tests for a dynamic regulation of camp openness based on evaluation of $R0$. With this, a weekly $R0$ is determined and based on predefined thresholds (see section 4.2.4) a more/less strict lockdown is imposed. The model results are depicted in figure 7.3 and further analysis of this experiment can be found in appendix G.1.2.



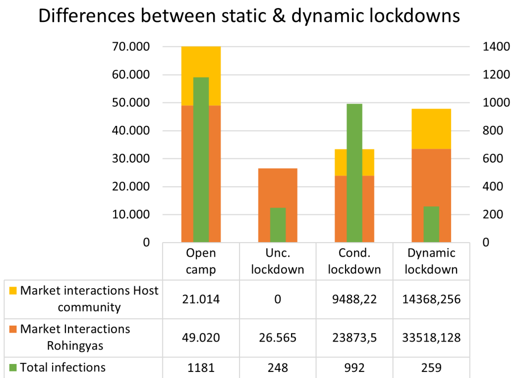
(a) Infections with Ro evaluation **(b)** Infections vs. interactions

Figure 7.3: Number of interactions for dynamic camp openness, based on reproduction number $R0$ for the number of infections (300 and 400 runs)

The results of dynamic camp openness show two mention-worthy outcomes. Firstly, a dynamic regulation of camp openness has a significant impact on further reducing infections in the initial 30 days of study. Namely, the infection trajectory becomes more balanced in this period (see figure 7.3a), which indicates a higher control over a large outbreak in that period. Different levels of strictness were measured for $R0$ evaluation (see appendix G.1.2), but this did not show a significant result. Secondly, the total number of infections can be significantly reduced, whilst keeping a high number of interactions possible. Namely, the reduction of infections is 55% for dynamic camp openness compared to an reduction of 15% for a conditional lockdown, whilst a dynamic camp openness allows for significantly more interactive freedom (80%) can be maintained compared to as static conditional lockdown (65%). Here, percentual reductions of interactions are compared to a fully open camp. This is illustrated in figure 7.3b, which shows a regression line for average interactions versus infections for a static and dynamic camp openness regulation. These regression line address the first effective trade-off for infections and interactions, with an improvement of reduced infections per interaction by approximately 62%.

7.3.3 Sub-conclusion: Effect of Camp Openness

It can be concluded from previous sections the imposing of different types of lockdowns or other movement restricting measures reduces infections significantly (see figure 7.4). For a static camp openness regulation, infections can be further decreased but with implications for interactive freedom. This interactive freedom can be guaranteed more when applying dynamic regulation of camp openness. Here, a first effective trade-off for infections and interactions exists, as more interactive freedom can be created whilst keeping infections constant. Therefore, when next sections focus on the analyses with a dynamic implementation of camp openness.



	Open camp	Unc. lockdown	Cond. lockdown	Dynamic lockdown
Market interactions Host community	21.014	0	9488,22	14368,256
Market Interactions Rohingyas	49.020	26.565	23873,5	33518,128
Total infections	1181	248	992	259

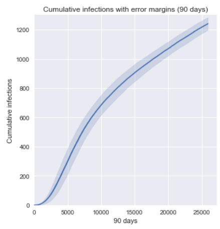
Figure 7.4: Differences between static & dynamic lockdowns for refugee-host interactions at both types of markets (average model results based on 400 model runs)

7.4 TESTING MODEL PARAMETERS FOR VACCINE ALLOCATION STRATEGIES

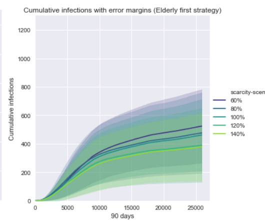
As an off-set against movement restrictions for limited camp openness, vaccine allocation strategies are applied. Vaccines are allocated through five prioritization strategies, further vary over its 1) availability (scarcity), 2) efficacy and 3) infectiousness. Vaccine availability is varied over a range of 40% below and above its baseline. Vaccine efficacy is analysed for 100% and 90%. Vaccine infectiousness indicates the infectiousness of vaccinated and infected individuals.

7.4.1 Comparing Strategies on Infections, Uncertainty & Scarcity Sensitivity

When applying different allocation strategies, different infection trajectories and solution spaces can be witnessed. When comparing these trajectories and total numbers of infections which results from these (see figure 7.5), most important differences with the base case model relate to the total infections, its trajectory and its uncertainty space. The application of vaccines (with 100% efficacy) results in a significantly lower number of infections, but with higher outcome uncertainty. The bandwidths indicate the standard deviation for infections, indicating an average error margin for distributing vaccines of approximately 110 infections. This is relatively high on a population of approximately 1100 individuals, and shows a relative high range of possible infections following from each strategy. Although outcomes of each strategy are relatively uncertain, each strategy is significantly effective for reducing the total number of infections compared to the base case. Within the whole solution space a reduction of infections compared to the base case can be guaranteed for each strategy. The main reason for this is the slower spread of infections in the initial 30 days.

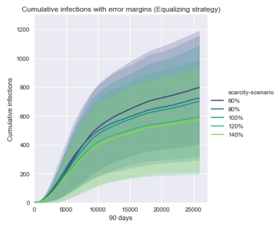


(a) Base case

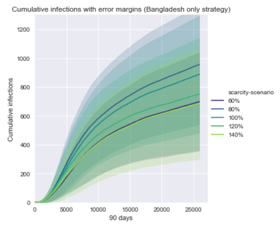


(b) Elderly First

(c) Children first



(d) Equalizing



(e) Bangladesh only

(f) Transmission group

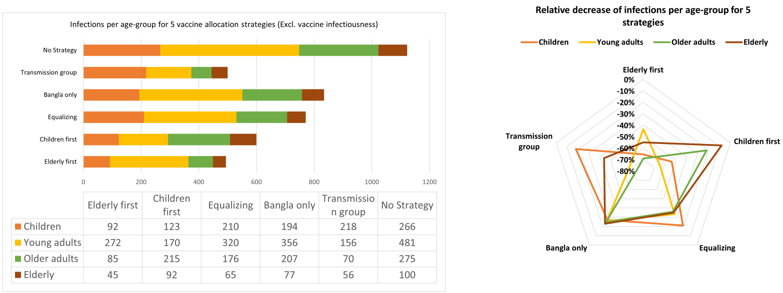
Figure 7.5: Comparing vaccine allocation strategies & uncertainty space for the: (a) base case (no vaccines) and (b-f) five allocation strategies (600 runs)

Comparing the strategies, two main differences exist. Firstly, strategies differ in effectiveness for reducing infections. The application of an EF strategy or TG strategy are most effective, resulting in an reduction of infections by 65% and 63% respectively, followed by prioritizing children (45%), equal access to vaccines (34%) and not vaccinating Rohingyas (23%). Here, infections are averaged over 100 runs per strategy. Secondly, the strategies differ in their sensitivity to vaccine scarcity. When increasing vaccine availability, only the EF strategy & TG strategy become significantly more effective. For the other strategies this effect is less visible (see appendix G.2), which is due to the fact these strategies include the lowest share of vaccinated individuals with a high force of infection. This is further discussed in chapter 8.

7.4.2 Comparing Strategies on Infections per Age-group

As different age-groups have age-specific characteristics for the development of COVID-19 , vaccine allocation strategies can be compared for age. Figure 7.6 shows the division of infections over four age-groups, both percentual and absolute.

Comparing the strategies, some interesting insights follow of which three are discussed. Firstly, there is a trade-off between the EF strategy and TG strategy strategies when for age-based reduction of infections for young-adults (18-40 years) and children (< 18 years): the TG strategy is effective for reducing infections among young adults, which can be compensated by the EF strategy which is equally effective for reducing infections amongst children. The latter conclusion seems paradoxical as it results from prioritizing elderly, but can be explained by the fact that the share of infected children is relatively low and the high-risk transmission groups are vaccinated. This is also the reason why the CF strategy is relatetively less effective, as figure 7.6b shows a lower effectiveness for reducing infections every age group. Namely, when children with low infectiousness are vaccinated first, the infection trajectory for other age-groups can still develop, which results in smaller effectiveness in this strategy. The same holds for the EQ strategy: although age-groups are equally vaccinated, the drop of infections for elderly and adults



	Elderly first	Children first	Equalizing	Bangla only	Transmission group	No Strategy
Children	92	123	210	194	218	266
Young adults	272	170	320	356	156	481
Older adults	85	215	176	207	70	275
Elderly	45	92	65	77	56	100

(a) Absolute Infections **(b)** Percentual decrease

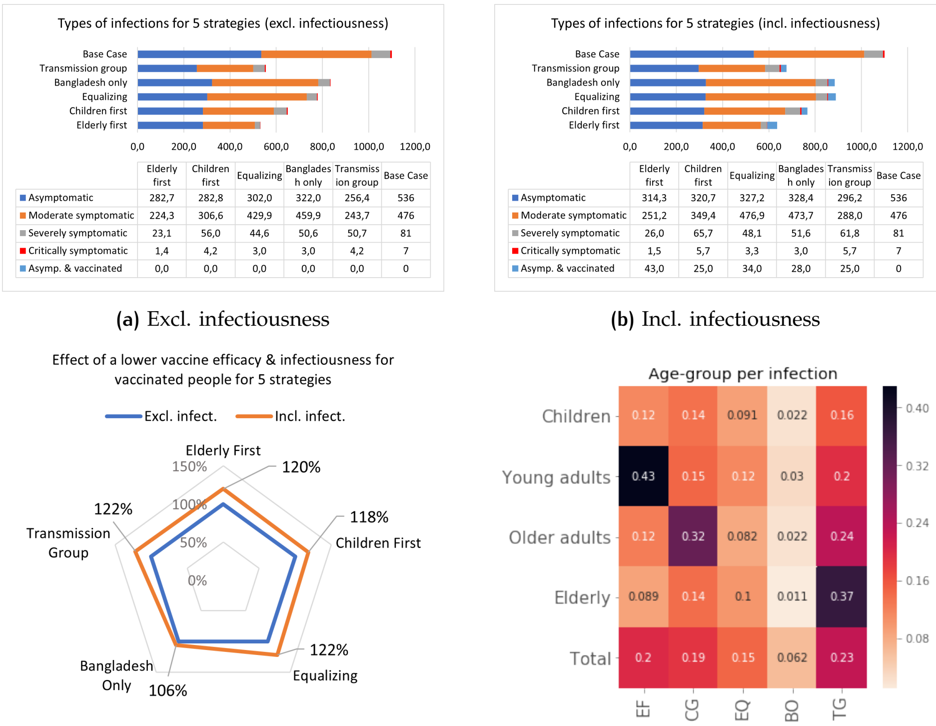
Figure 7.6: Infections per age-group for five vaccine allocation strategies: (a) absolute differences per age group compared to base case & (b) percentual decrease of infections per age-group (average model results based on 100 model runs)

is higher as these age-groups are more susceptible for an infection. A benefit for the EQ strategy is its relative low share of infections amongst young adults, but this effect is the same for the Transmission strategy. Secondly, the EF strategy (-53%) and TG strategy (-42%) are most effective for reducing absolute numbers of infections for elderly. Both strategies show the strongest reduction in this age-group, which is a high-risk group regarding health-related issues. Other strategies are less effective, which in combination with their lower effectiveness in general are less desirable. Also, both strategies show most effective reduction of infections in the adult age-group (18-60 years), which represent most economic value. Thirdly, the EQ strategy and BO strategy have littlest effect compared to the other strategies. Both relatively and in an absolute sense, these strategies are ineffective: as can be derived from figure 7.6a, the share of young and older adults infected is high, which indicates insufficient individuals are vaccinated with high risks of transmission. The difference here is the EQ strategy does not reach a sufficient share of the population with a high-risk of transmission, whereas the BO strategy lack sufficient vaccines distributed over the population.

7.4.3 Comparing Strategies on Types of Infections & Vaccine Infectiousness

The strategies also differ over four different types of infections. Here, two scenarios are measured for vaccine efficacy and vaccine infectiousness: an efficacy of 100% excluding infectiousness versus 90% including infectiousness. Starting with the effect of vaccines excluding infectiousness, a reduction of infections for every type of infection can be registered compared to a base model. Here, symptomatic infections are most significantly reduced by the EF strategy (-68%); the relative effectiveness is comparable for the TG strategy is comparable, but asymptomatic infections (-52%) are reduced instead. See figure 7.7a.

When vaccinated individuals are infectious, results are different comparing strategies to the base case and to other strategies. Vaccinated individuals who are infectious to others result in an average 16% higher infection rate. This difference is most significant for the TG strategy and EF strategy, as can be derived from figure 7.7c. Infections for the BO strategy is relatively unaffected, as infections are only 6% higher. To understand this difference, two factors play a main role: the *risk of transmission* and the *absolute number of vaccines* allocated. A low absolute number of vaccines allocated also reduces the relative chance of being infected by an infectious vaccinated individual. This means, vaccine-infectiousness is most strong in the last 60 days. Here, the percentage of vaccinated people is highest, which can be illustrated with an example. The BO strategy has a significant low share of vaccinated people (74% less compared to when Rohingyas are included), which explains the low sensitivity of this strategy to vaccine infectiousness. This is illustrated by studying the infection trajectories for both strategies in figures G.3g & G.6g. The second reason relates to the risk of transmission. If the share of infectious & vaccinated individuals is high for sub-groups with a high risk of transmission, infections develop faster. In this research, the risk of transmission is determined based on age: younger adults are most active inside the camp. Therefore, the relative effectiveness for vaccine infectiousness can best be understood by studying the relative increase of infections per age-group (see figure 7.7d). This figure shows to pitfalls of the TG strategy, EF strategy and CF strategy, as higher percentages of infection occur in non-vaccinated age-groups. For example, the prioritizing of Transmission groups (younger adults) strongly increases infections among older adults (24%) and elderly (37%).



	Elderly first	Children first	Equalizing	Bangladesh only	Transmission group	Base Case
Asymptomatic	282,7	282,8	302,0	322,0	256,4	536
Moderate symptomatic	224,3	306,6	429,9	459,9	243,7	476
Severely symptomatic	23,1	56,0	44,6	50,6	50,7	81
Critically symptomatic	1,4	4,2	3,0	3,0	4,2	7
Asymp. & vaccinated	0,0	0,0	0,0	0,0	0,0	0

(a) Excl. infectiousness

	Elderly first	Children first	Equalizing	Bangladesh only	Transmission group	Base Case
Asymptomatic	314,3	320,7	327,2	328,4	296,2	536
Moderate symptomatic	251,2	349,4	476,9	473,7	288,0	476
Severely symptomatic	26,0	65,7	48,1	51,6	61,8	81
Critically symptomatic	1,5	5,7	3,3	3,0	5,7	7
Asymp. & vaccinated	43,0	25,0	34,0	28,0	25,0	0

(b) Incl. infectiousness

(c) Relative difference

	EF	CG	EQ	BO	TG
Children	0.12	0.14	0.091	0.022	0.16
Young adults	0.43	0.15	0.12	0.03	0.2
Older adults	0.12	0.32	0.082	0.022	0.24
Elderly	0.089	0.14	0.1	0.011	0.37
Total	0.2	0.19	0.15	0.062	0.23

(d) Infected age-groups

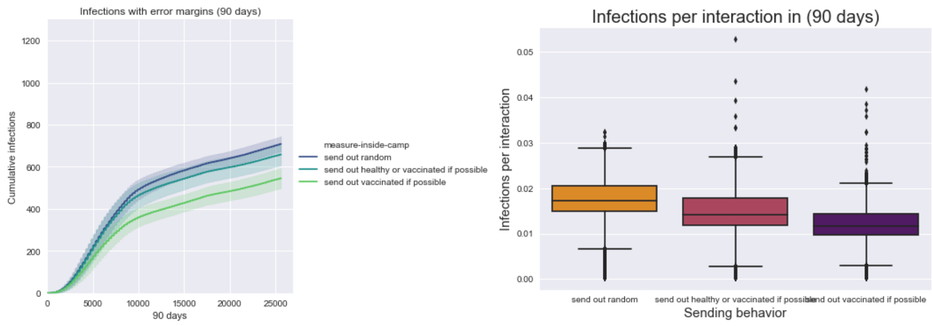
Figure 7.7: Types of infections for the base case and 5 allocation strategies, excl. vs incl. vaccine infectiousness (vaccine efficacy 90%, average model results for 200 runs per strategy)

7.5 DYNAMICS BETWEEN CAMP OPENNESS & VACCINE ALLOCATION STRATEGIES

Based on the insights from previous sections, a fourth round of experiments is carried out with a focus on enforcing trade-offs between infections and interactions. Here, experiments are carried out with a focus on dynamic camp openness for the four types of conditional lockdowns, giving vaccinated individuals more interactive freedom and how vaccine allocation strategies affect these. The aim here is to study whether this sets a more effective trade-off for (types of) infections and interactions. Lastly, as the absolute reduction of infections for the EQ strategy and BO strategy is relatively low, these strategies are not further analysed.

7.5.1 Interactive Freedom for Vaccinated Refugees

The isolated effect of allowing only vaccinated individuals at shared facilities was measured and is shown in figure 7.8. The experiment shows how the allowing of vaccinated individuals can not only significantly reduce infections (as showin in figure 7.8b), but can also effectively allow for more interactive freedom. This is shown in figure 7.8a, which shows the number of infections as a result of rule-compliant individuals (i.e.which only leave their shelter when being compliant and vaccinated). Next sections build forth on the approach of lending more interactive freedom to vaccinated individuals.



(a) Infection trajectory **(b)** Infections per interaction

Figure 7.8: Relative effect of only allowing (compliant) vaccinated individuals at shared locations (180 runs)

7.5.2 General trade-off: Implementation of dynamic lockdowns & allocating vaccines

An experiment was carried out combining a dynamic implementation of lockdowns in combination with the implementation of the three strategies (see table F.6 for parameter set-up). Here, based on weekly infections the camp is opened and closed for visitors and in-camp markets are closed for non-vaccinated individuals. The result of this experiment is shown in figure 7.9 (see appendix G.4 for other strategies).

(a) Dynamic Camp Open. **(b)** Combined **(c)** Infections vs interactions

Figure 7.9: Pattern analysis for combined parameter effects on cumulative infections for: (a) Dynamic Camp Openness (no vaccines), (b) Dynamic Camp Openness & the EF strategy & (c) infections vs. interactions for this combination (600 runs)

The results shows a significantly stronger effect for a combined application of dynamic camp openness and vaccines. The application of vaccines further reduces infections in the initial 30 days of infections, but also creates more interactive freedom: compared to an unconditional, static lockdown the reduction of infections is 89% (EF strategy), 87% (TG strategy) 82% (CF strategy), 75% (EQ strategy) and 65% (BO strategy) and 47% (no strategy). The main benefits for this combination is reflected in the initial 30 days. Here, a large outbreak is prevented and no strict lockdowns have to be imposed. Vaccines have a significant effect on this reduction, as is further analysed in appendix G.5. The main insight from this experiment is the finding of a **first trade-off** for infections and interactions: combining camp openness restrictions and vaccines (trough any strategy), significant infections can be reduced for the a constant level interactive freedom. In next sections, more specific types of dynamic camp openness are tested for different strategies. Here, camp openness is defined trough 2 lenses: an economic lens and a health-based lens as an offset. These are conducted to test whether the relative effectiveness of different strategies can be improved.

7.5.3 Specific trade-off for increasing economic interactions

A last round of experiments was carried out with an economic approach, and is compared with a health-focused approach. Trough an economic approach, it was tested whether economic interactions can be increased when allowing vaccinated people at the markets. Here, focus is set on increasing interactions at in-camp markets and at the vicinity market, for younger adults. Also, the effect of allowing host communities in the camp is measured. To compare the strategies, a light is shed on these outcomes through an health-focused lens (i.e.minimizing infections). A summary of these experiments is shown in figure 7.10. For a complete overview of these results, see appendix G.5.

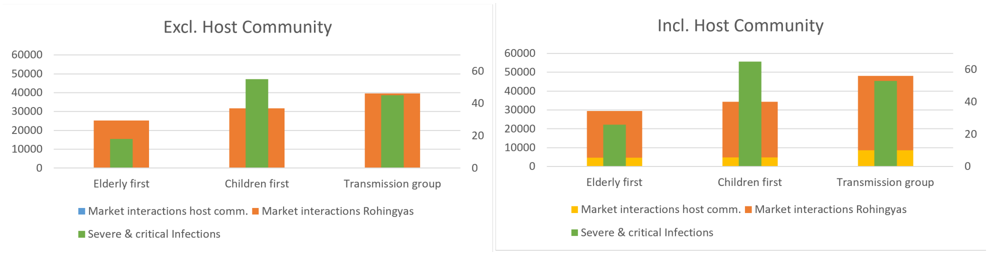
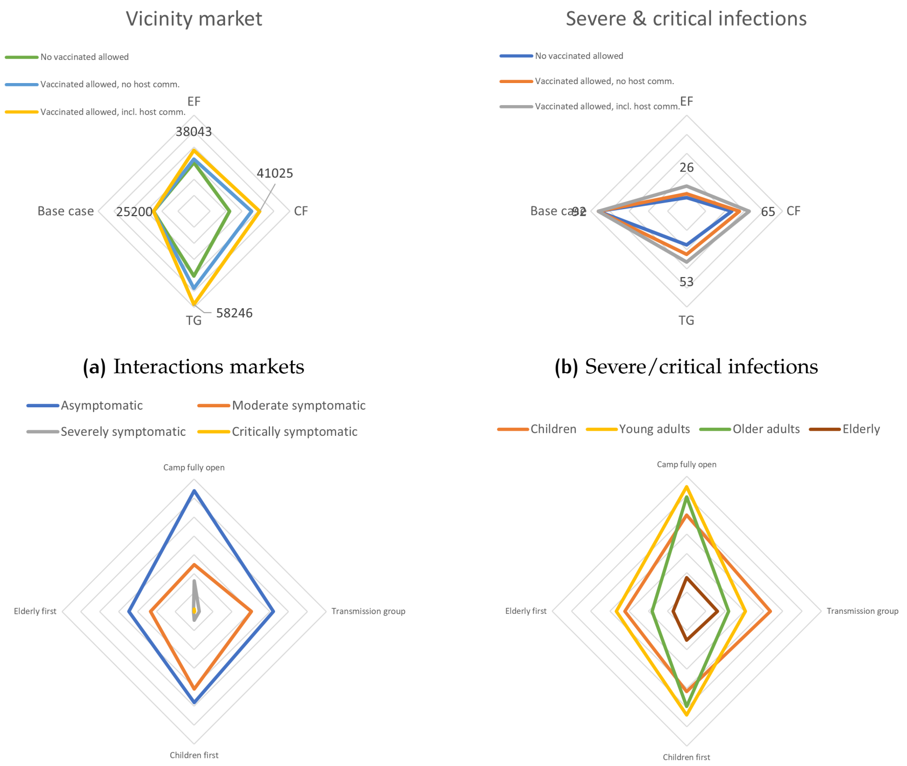


Figure 7.10: Model results for always allowing vaccinated people & host communities for maximizing economic activity (average model results from 400 runs)

The results show that economic interactions can significantly be increased if vaccinated people are allowed markets at all times. On average, a 27% more interactions can be allowed at the markets, which can be raised by 35% if host communities are allowed into the camp. This is significant both in relative matters and in absolute interactions: economic interactions can on average be raised by 108 or 204 interactions per household over 90 days, respectively including or excluding host communities from markets. Comparing the strategies, economic interactions can most significantly be increased if young adults are prioritized for vaccines through the TG strategy. On average, this strategy raises interactions over 75%, or even more than doubled (114%) if host communities are allowed. Other strategies also create more economic freedom, but this effect less strong.

However, allowing more interactions shows to also increase infections. Including vaccinated individuals shows the reduction of severe and critical infections is significantly lower for each strategy, considering the potential infectiousness of vaccinated individuals and for vaccine efficacy of 90%. On average, allowing for more economic freedom causes an increase of 22% and 50% severe/critical infections, respectively excluding or including host communities. The increase of infections is highest at the vicinity market, which is more frequently visited by host communities. Comparing the strategies, the relative reduction of severe/critical infections is relatively low for the TG strategy and CF strategy: more than double compared to the EF strategy. This can be explained as the share of high-risk age-groups remain non-vaccinated.

The these results show the main trade-off for creating more economic freedom is the increase of severe/critical infections as a pitfall. On one hand, allowing more economic freedom for vaccinated people and host communities can most effectively be created when applying the TG strategy (figure 7.11a). However, this strategy is less effective for reducing severe and critical infections (see figure 7.11b). As an offset, a last experiment was carried out to reduce this effect by studying the relative decrease of severe/critical infections for keeping elderly at home. Here, the idea was to test if a limited camp openness measure for a high-risk age-group can also effectively reduce severe/critical infections, which is the case as shown in figures 7.11c & 7.11d.



(a) Interactions markets **(b)** Severe/critical infections

(c) Keep elderly home **(d)** Infections per age

Figure 7.11: Relative reduction of four types of infections for: (a) closing markets & (b) keeping elderly home (average model results from 400 runs)

7.6 CONCLUSION

Chapter 7 presented the model results from the experiments which were carried out in this study, and gave an answer to sub-question 5 in this research: *How can the dynamics between refugee-host interactions, the spread of COVID-19 and vaccine allocation strategies be explained with an agent-based model?* To do so, four types of experiments were carried out: for studying a (a) base case, the single effect of (b) camp openness regulation, and (c) different vaccine allocation strategies and (d) the dynamics between these. Model results can be summarized as follows. The base case shows a fast outbreak of infections, which mostly concentrated in the initial 30 days. The influence of host community people bringing in the virus here is crucial. In case of an outbreak, the largest share of the population covers highly transmitting young adults (47%), followed by older adults (26%), children (21%) and elderly (6%). Resulting from their infections, a small fraction of the population (7,7%) faces a severe or critical infection.

Both the implementation of limited camp openness and vaccines can reduce these infections. Limited camp openness is most effective when applied through a dynamic approach: when opening/closing the camp based on infection-rates, infections per interaction can further be reduced by 44% compared to a static approach. The application of vaccines is even more effective. Here, it is most effective to reduce infections per interaction by applying the EF strategy (-55%) or TG strategy (-53%), followed by the CF strategy (-45%), EQ strategy (-34%) and BO strategy (-23%). The main reason for the effectiveness of the first two strategies is their larger share of vaccinated (protected) age-groups with a high-risk transmission profile (i.e. adults). However, this effect is significantly smaller when vaccinated individuals are still infectious to others. Other important differences between strategies relate to types of infections and infected age-groups. To control and reduce total infections in general, it is most effective to prioritize elderly (> 60 years) or transmission groups (young adults, 18-40 years). Vaccinating children first, creating equal access for vaccines or excluding Rohingyas from the vaccination program is less effective.

Building forth on most effective strategies, it is most effective to prioritize elderly from a health-based perspective. In this age-group, the largest share (60%) of severely and critically symptomatic infection is registered. To improve economic benefits expressed in maximizing refugee-host interactions, it is most effective to prioritize transmission groups (young and older adults), especially when vaccinated refugees and host communities are always allowed at markets. This effectiveness is lower if vaccinated individuals can still be infectious to others, as the share of vaccinated age-groups with a high-risk transmission profile is high and the share of high-risk vulnerability people is also high. An important conclusion is the implicit trade-off between the Elderly first and Transmission group strategies, which are in general most effective to control COVID-19 infections. The benefits for of the TG strategy are mainly economic, as this strategy allows for 8% more refugee-host interactions. However, the number of severe and critical cases for this strategy are more than three times higher for this strategy compared to the EF strategy.

Lastly, vaccine allocation strategies and camp openness are implemented in combination. Regardless the prioritization strategy, infections can on average be further decreased by 32%. Through an economic lens (focusing on maximizing interactions at markets for young adults), the TG strategy can create more economic freedom. Here, allowing vaccinated people at any time can stimulate the interactions at markets by 75% and can be more than doubled if also host communities can be allowed. The consequence here is a higher share of severe/critically symptomatic infections. In chapter 8, these model results are further analyzed and interpreted for policy advise.

8 VALIDATION & INTERPRETATION OF MODEL OUTCOMES

In chapter 8, the model results from previous chapter are validated an interpreted. In this way, an answer is formulated to the last sub-question of this research: *How can the outcomes of this study be translated to an effective strategy for COVID-19 vaccine allocation in a refugee camp?* This chapter starts with a validation of the model outcomes in section 8.1. Then, model outcomes for the base case are interpreted in section 8.2, followed by the interpretation of camp openness regulation and vaccine allocation strategies in section 8.3 and 8.4. In section 8.6, results and their interpretation are put into a broader context of real-world application for the Rohingyas. All sections are summarized and concluded in section 8.7.

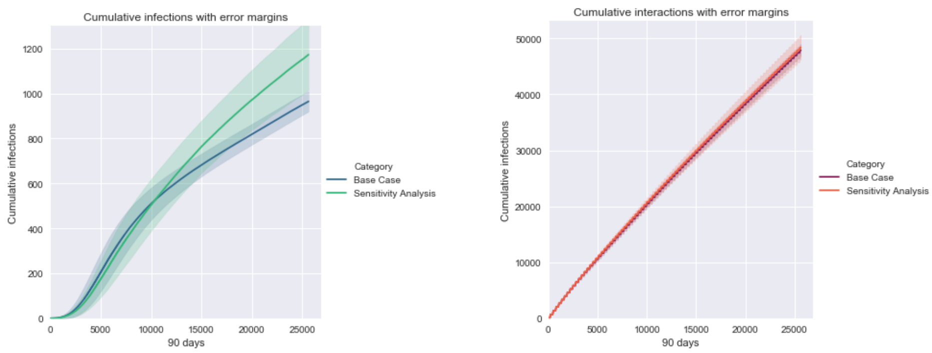
8.1 MODEL VALIDATION

Model validation answers to the question whether the model results are representative to the real-world phenomenons of study. Three techniques are used to check the validity of the model, which assess whether the outcomes of this model can be translated into valuable, useful and meaningful insights for real-world decision-making: a sensitivity analysis, a literature comparison and validation by expert interviews.

8.1.1 Sensitivity Analysis

A first type of model validation which has been performed is a sensitivity analysis. With a sensitivity analysis, complex dynamics in ABM models can better be understood [Ligmann-Zielinska et al., 2014] and the effect of parameters based on critical assumptions can be tested for robustness or sensitivity [Leamer, 1983]. This is valuable for this research, as in the base model several parameters exist which were not varied with during the model runs but were based on assumptions or estimations from secondary research or data sources. These parameters are the *force of transmission*, *symptomatic-rate*, *contact-rate*, *time of being sick*, *re-infectious time* and the *level of non-compliance* (i.e.for stay-at-home when sick or not being vaccinated). These parameters were chosen, as these were not varied with in the base model. However, as they are expected to influence the infection & interaction trajectory, it is tested how sensible the model is for these parameters. To do so, two experiments were performed and compared with 500 simulations each. In the first experiment, the base model was run using the five parameters with their original values. In the second experiment, these parameters were varied over a range of 0%-50% added to their original value (see table F.7), leaving other model parameters fixed (see table F.2). Results are shown in figure 8.1. From this, it can be concluded a higher sensitivity is measured for the infection trajectory if the sensitivity parameters are increased. Interactions are insignificantly affected, which indicates a relatively insensitive behavior of refugees to interact, regardless the factor of infected people.

To understand the increased effect on infections, figure 8.2 shows correlations of three types of infections and three places of infections. From this, it can be concluded four parameters have significant influence. Regarding cumulative numbers of infections, an increased level of non-compliance and a high force of infection cause an increase of infections. The force of infection mainly stimulates symptomatic infections, which is also concluded in other studies. For example, Davies et al. [2021] stated age-adjusted forces of transmissions for COVID-19 are estimated over a 43-82% range. In this research, age and force of transmission were also linked. Secondly, the rates of symptomatic infections shows to be insensitive to create more infections. This is not in line with other studies,



(a) Trajectory of infections

(b) Trajectory of interactions

Figure 8.1: Sensitivity Analysis: trajectory of infection & interactions (1000 runs)

which conclude a higher infectiousness for symptomatic individuals (e.g. Swan et al. [2021]), which was not assumed in this research. A more important factor here is the contact rate, which indicates the high sensitivity of more infections if more interactions are allowed in the model. Here, infections at the markets are most sensitive. Lastly, the level of non-compliance shows to be a sensitive factor for raising the infection trajectory. This means, an important factor deciding the number of interactions is the individual choice of refugees to live up with the rules of isolation. This was concluded earlier for vaccinated individuals in 7.5.1, but also yields for compliance to stay-at-home when being infected (further analysed in appendix G.3.2).

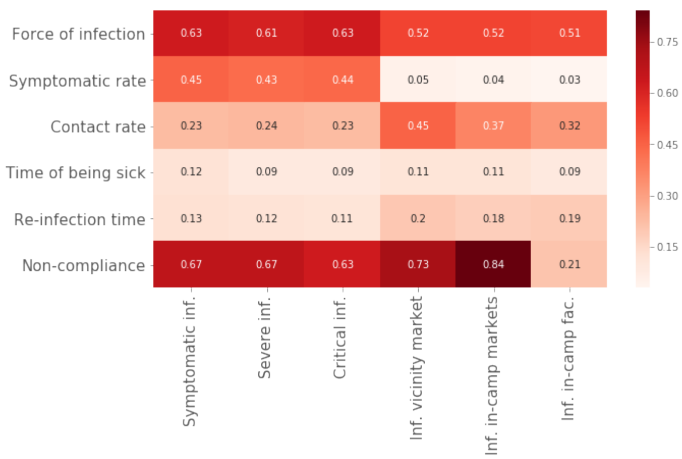


Figure 8.2: Sensitivity Analysis for five uncertain model parameters (1000 runs)

From this sensitivity analysis, it can be concluded the model is relatively sensitive to the number of interactions. In other words, individual's choice to leave their shelter is not affected by the current state of COVID-19 infections. For the trajectory of infections, a higher sensitivity is measured which implicates a lower robustness of the model results regarding this KPI.

8.1.2 Validation by Comparing Literature Studies & Current Practices

A second type of model validation is the comparison of the model results with outcomes of other studies an current practices on related topics. With this, higher validity of the model outcomes are concluded if a similar conclusion is drawn in another study [Van Dam et al., 2012], even if these studies have a different formulated goal [Xu et al., 2003]. Academic literature has been studied on the following topics: (a) the spread of COVID-19 in context of the Rohingya refugee camps, (b) the effectiveness of camp openness measures in other refugee camps and (c) results and conclusions about vaccine allocation strategies in other studies which are comparable to the context of Rohingya camps.

Literature comparison on the Spread COVID-19 in Refugee Camps

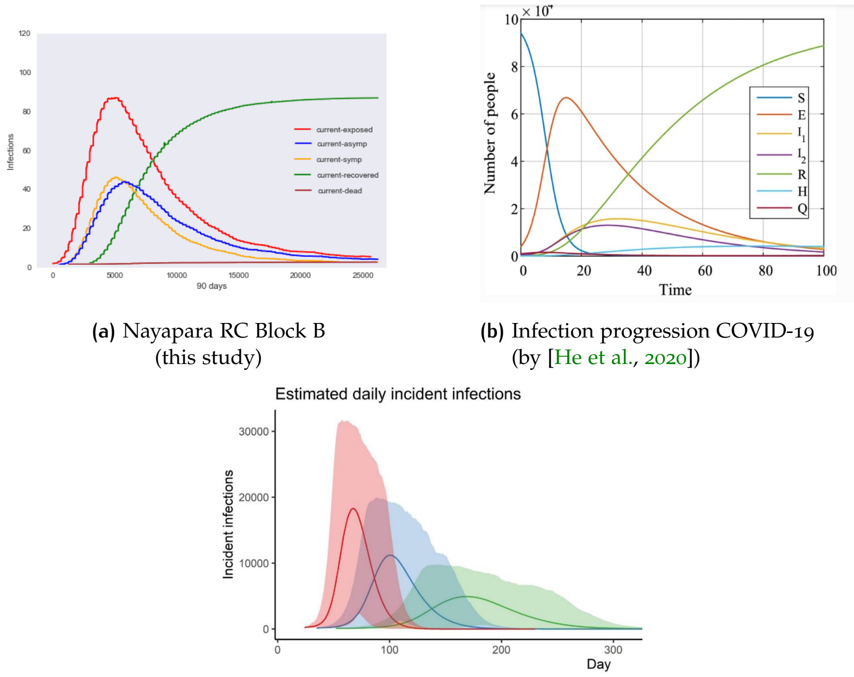
Up to the writers knowledge, two studies focused on the spread of COVID-19 in a refugee camp. Hernandez-Suarez et al. [2020] focused on the Za'atari refugee camp in Jordan, and researched the COVID-19 trajectory here, influenced by non-pharmaceutical meaures with a SIR model (which is a simpler version of the SEASR-model which is used this study). Hernandez-Suarez et al. estimates an approximate 95% of the Za'atari refugee camp will be infected, but with low mortality coverage (0.02%). This is similar for this study, as an estimated 110% of the population will be infected. This difference can be explained as the model in this study also considers *re-infection* as an important factor. Also, mortality rates are comparable and with the same line of reasoning: both refugee camps are characterized by relatively young populations (for both populations, 60% is younger than 20 years Hernandez-Suarez et al. [2020]; Lopez-Pena et al. [2020]). Where this study performs similar as well, is the estimated speed of COVID-19's spread. Hernandez-Suarez et al. [2020] estimates, 75% of the total population will be infected within 8 weeks, without any policy interventions, which is the exact estimation of this study within that period. However, when studying the COVID-19 Dashboard in Cox's Bazar, this might be an overestimation, as registered numbers of COVID-19 cases are lower.

A second study by Truelove et al. [2020] estimated the COVID-19 trajectory for 600.000 Rohingyas (see figure 8.3c. In this study, a SEIR-model was applied as well, and concluded *"a large-scale outbreak is likely after a single introduction of the virus into the camp"* [Truelove et al., 2020, p.1], with an approximate 98% infection coverage within 12 months. This is similar to the conclusion in this study (see figure 8.3a), although the speed of spread might be overestimated in this research (as this was concluded for the period of 3 months). A last validation for the COVID-19 trajectory, is the simple comparison of theoretical outcomes of a SEIR model by He et al. [2020] with the outcomes of this model applied to the Rohingya cases (see 8.3a and 8.3b). To make this comparison, 50 runs were performed in the model without re-infections. As can be seen in the figures, both trajectories are comparable.

Comparison of non-vaccine related COVID-19 measures in refugee camps

For the base model, several effects were tested as these were assumed to affect the progress of COVID-19's spread in the Nayapara RC camp. Here, two factors were assumed to have an effect: (a) bottom-up decisions by refugees to comply with isolation rules (relating to health and vaccination status) and (b) governmental top-down camp openness regulation. Relating the first factor, this research is comparable to other studies which also stress the importance of home isolation to better control infections. Bullock et al. [2021] estimates a small reduction of infections if people with mild symptoms stay home, but a stronger effect if symptomatic individuals isolate. In this research, this difference was not made. As asymptomatic individuals are assumed as infectious as symptomatic individuals, this study might overestimate the effect of compliance for isolation for asymptomatic individuals. Secondly, a relatively high level of compliance was used in the model. This is not in line with insights from Wright et al. [2020], concluding a significantly lower level of compliance for poorer people. As Rohingya refugees are among the poorest, this might be an overestimation. However, from expert interviews it was concluded Rohingya refugees the level of compliance to stay home in case of an infection is high. This indicates the outcomes for this study regarding stay-at-home compliance is representative, although cannot be validated with an academic study.

Relating the second factor, the effect of lockdown measures is validated. For this, the effect of a full/unconditional lockdown in Bangladesh as researched by Islam et al. [2020] and the effect of partially allowing for more capacity at shared facilities as researched by Bullock et al. [2021] (in this study: a conditional lockdown) were compared with this study, as shown in figure 8.4. The outcomes of other studies indicate a similar ef-



(a) Nayapara RC Block B (this study)

(b) Infection progression COVID-19 (by [He et al., 2020])

(c) 600.000 Rohingyas (by [Truelove et al., 2020])

Figure 8.3: A case study and theoretically-based comparison of the trajectories using a SEIR infection model: (a) for this study, (b) for theoretical outcomes & (c) for estimated outcomes by Truelove et al. [2020]

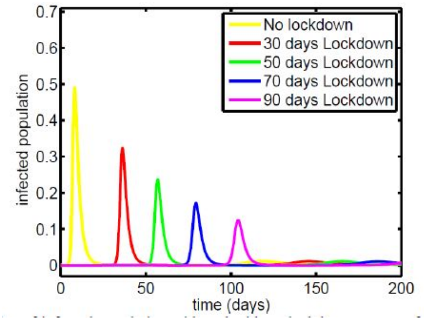
fect of different types of lockdowns. The effect of a 90-day lockdown has an effect of an 85% reduction of COVID-19 cases, estimated by [Islam et al., 2020], compared with an approximate 75% reduction for the static, unconditional lockdown for this study. These results implicate a valid representation. The effect of a conditional lockdown is compared with Bullock et al. [2021]'s estimated effect of reopening learning centres inside the camps versus a full lockdown with all shared facilities closed (as indicated in the right and left graph respectively, in figure 8.4c). The figure indicates the partial reopening of shared facilities will triple the number of infections, which is similar for conditionally allowing 50% more hosting communities in this study, reducing infections by approximately 350%.

Whether these results are valid is still hard to state with high certainty, as contexts differ: generalizing a reseach by Islam et al. [2020] for Bangladesh to the context of the Rohingyas and the comparison of partially opening the camp for host communities and reopening learning centres is arguable. However, both studies show a good indication for the effect of a(n) (un)conditional lockdown, which is a valuable conclusion for stating the validity of this research.

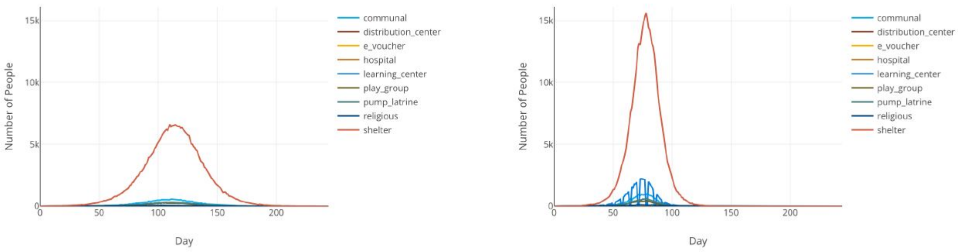
Vaccine allocation strategies

Lastly, outcomes of other studies on vaccine allocation strategies are used to validate the outcomes of this study. Foy et al. [2021] studied the effect of age-based vaccine allocation in India, which can be compared to the Rohingya context as both studies consider highly populated areas. In their studies, some conclusion are similar to this study. A first similar conclusion is the importance of other, non-pharmaceutical measures in combination with vaccines for a maximum effect to reduce infections (see figure G.16). A second similarity of both studies is the importance of a 'fast roll-out' of vaccines [Foy et al., 2021] and the conclusion in this study the main that the greatest benefits of vaccinations are gained in the initial 30 days. Foy et al. [2021] concludes the differences between prioritization strategies are less significant if vaccines are efficiently distributed. This also yields in this study, as illustrated in figure 8.5: faster vaccination (blue lines)

(a) Cumulative infections (this study)



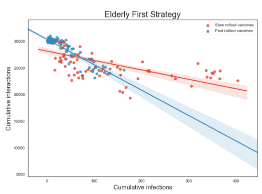
(b) Infection progression full lockdown (by [Islam et al., 2020])



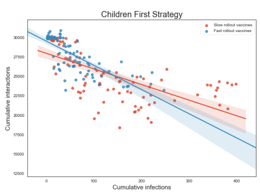
(c) Infection progression conditional lockdown (by [Bullock et al., 2021])

Figure 8.4: Validation of the effect of a(n) (un)conditional lockdown on infections: (a) Nayapara RC Block B (this study), (b) for a full lockdown, measured for Bangladesh (by Islam et al. [2020]) and (c) the effect of reopened learning centres in the Rohingya camps

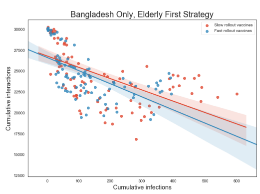
shows little difference between the strategies compared to slow vaccination (red lines).



(a) Elderly first



(b) Children first



(c) Bangladesh only

Figure 8.5: Smaller difference between vaccine allocation strategies for a faster roll-out of vaccines shown for the: (a) best (EF strategy), (b) medium (CF strategy) and (c) worst performing allocation strategies (BO strategy)

Regarding the differences between vaccine allocation strategies, several studies are compared. A first similarity is the conclusion by Gupta and Morain [2021] and Shim [2021], who conclude vaccine allocation which focuses on reducing morbidity and mortality rates is most effective when prioritizing elderly above 50, whereas economic benefits are highest if transmission groups are prioritized. This is similar to model results in this research, as severe/critical infections can be reduced most effectively if elderly above 60 years are vaccinated and for stimulating economic interactions, vaccinating transmission groups is more effective. The latter conclusion was also drawn by Foy et al. [2021], concluding the prioritizing of young adults (20-40 years) is most effective for reducing infections in India. This corresponds with the outcomes in this research, as prioritizing young adults was categorized as an effective strategy. Also, similar to this study, is the conclusion by Gupta and Morain [2021] that the EQ strategy is a less effective strategy for controlling the spread of COVID-19. However, Duijzer et al. [2018] concludes an equal access could be effective for reducing infections at home (i.e.as relatively a higher share of household members are vaccinated). This could not be assessed in this research, as no infections at home were assumed. For the validation of the ineffectiveness of vaccinating the Bangladesh population only, which strategy performed relatively ineffective, no literature can be found which can be used for validation of this strategy. However, Tuite et al. [2010] researched the effectiveness of fixed vs. flexible vaccine allocation strategies, where flexible allocation implied to reformulate a prioritization strategy if infections raise in other age-groups or geographical areas. The latter conclusion is also drawn by an evaluation of geography-based allocation strategies (see section 2.3.1). As the BO strategy excludes a the Rohingyas as a source of transmission, the same conclusion can be drawn as the effectiveness of this study performed low on both lowering infections and creating more economic freedom.

8.1.3 Expert Validation

A last type of model validation is performed through discussing model results with experts. To do so, an expert was interviewed with semi-structured questions and discussions about the model outcomes. Here, main focus was set on the likeliness of real-world representation of these results in context of the Rohingyas, and to discover potential over or underestimations of the results. From this expert interview, the main validation could take place for the base model. Namely, no clear indications can be given on the current practices related to the vaccines delivered at the time of writing this report. A summary of this expert validation can be found in appendix B.4. From expert validation, model outcomes were validated for the effect of: dynamic camp openness, the difference between a conditional vs. an unconditional lockdown expressed in the number of following infections, wearing mask compliance and stay-at-home compliance and for the number of interactions in the camp.

Starting with most accurate, valid outcomes of these discussions, it can be concluded both compliance to wearing masks and stay-at-home when sick are valid representations of the Rohingya camps. Firstly, several fieldwork observations by the expert and colleagues pointed out mask wearing compliance is low in the camp (estimated $< 30\%$), which represents the low effectiveness of masks as concluded in this study validly. Secondly, stay-at-home isolation is a more effective measure and compliance to also live according to this measure was intended in this study. These insights understate the validity of the little effect of wearing masks and high effect of staying home. Another valid model structure is the assessment of camp openness on a weekly basis. According to the expert, new measures imposed in the Rohingya camps is based on weekly infection rates, as done in the model for this study as well. Initially, this weekly assessment was assumed based on weak indications, but is validated with more strength after the interview.

A less valid component in the model is the differences in the infection trajectory estimated for an unconditional versus a conditional lockdown. According to the expert, no real 'unconditional' lockdown exists in context of the Rohingyas, as controlling people's movement is really hard in practice. Therefore, variations with different levels of conditional lockdowns sets a more valid representation of reality, which is a conflicting conclusion with the validation in section 8.1.2. Another less valid representation is the frequency of interaction at the bigger market, which was assumed on once every two days by each individual in the camp environment. However, in reality visiting markets is done more frequently. The expert estimates a daily visiting of the bigger market would be more valid. This implicates an underestimation on the number of infections in this study, as more frequent interactions also potentially lead to a faster spread of COVID-19 cases.

Overall, based on the expert interview, it can be concluded not every model component is a clear representation of reality in the Rohingya context. However, as also stressed by in the expert interviews, one should keep in mind the high level of uncertainty which is always a limitation for research in the Rohingya camps. Namely, many things go unnoticed or happen in informal settings. Also, research in context of COVID-19 which is needed for a validation check is hard, as doing research inside the camp environment was not possible for long.

8.2 INTERPRETATION OF BASE CASE

From the analysis of the base case model, some first insights were gained on the dynamics between infections and interactions in an open-system camp environment. A first insight from the base case model relates to the infection trajectory and the role of the host community influencing this. Results show a good indication of how COVID-19 develops in context of the Rohingya camps, and how the interactions with host communities can cause an outbreak of infections which is potentially large enough to infect everyone in the camp environment. Starting from at least one infection, regardless this is a refugee or someone from host communities, infections raise rapidly. Here, the outbreak is mainly concentrated around the first 30 days of the total period of 90 days. In this time, the number of infections reaches a tipping point, after which the growth of infections slows down. This is due to the fact that so many individuals get infected, recovered people form their own group immunity. This statement is based on model outcomes as shown in figure 7.1a, indicating over an infection coverage which reaches over a 100% of the total population in 90 days. These results can be interpreted as a baseline for the number of infections which could happen, in a situation no measures are imposed an individual refugees have little to no knowledge on measures for self-prevention and show the stressed importance of infection-reducing measures.

A second insight from the base case model relates to understanding *how* these infections happen and what role refugee-host interactions play here. The main source of infections was measured at the vicinity market (49%), followed by in-camp markets (38%) and in-camp facilities (14%). These model results can be interpreted in two ways: firstly, it can be concluded the number of facilities is an important factor guiding the chance to meet an infected person. In-camp facilities are most frequently visited by Rohingyas (80% of all Rohingya interactions), but a lower chance to get infected is registered. As the vicinity market concentrates around one location, there is a fairer chance of meeting someone here and therefore also is a higher source of infections. Secondly, the the role of the host community bringing in infections to the camp can be explained. Namely, in-camp facilities and the vicinity market are visited equally by Rohingyas, but infections are higher at the vicinity market. This is due to the higher numbers of host community people which enter the vicinity market (88%) and their relatively low participation at in-camp markets (12%).

A third insight relates to infections per age-group, which were mostly registered among younger adults and older adults. This stresses the assumption of their high-risk transmission profile, as their relative infection coverage is higher than for children and elderly. Covering only 35% of the total population, these age groups cover an approximate 73% of all infections. This is significantly more than for children, covering 60% of the population but only 21% of all infections. This also helps to explain the high share of infections at markets, as adult people are most represented here.

A last insight relates to the potential seriousness of a large outbreak from a health-based perspective. Studying the relative share of severe and symptomatic infections, an average 8% of the people . This is a worrying implication, stressing the importance of controlling the infection trajectory and limiting any type of interaction, especially when the outbreak is speedy. To illustrate that for further interpretation, on a population of 1 million Rohingyas an approximate 7.000 people would require medical assistance due to a severely symptomatic infection and 1.000 would be in need of being hospitalized.

Overall, the base case model gives a good indication what would happen if an open-system refugee camp is not regulated by any restrictions. The model shows what could happen as a result of thousands of social and economic interactions between the refugees and host communities both inside and outside the market. As the growth of infections and its share of severe/critically symptomatic infections is high, the urgent need for controlling infections is stressed. In the next sections, the (combined) role of camp openness restrictions and vaccines is discussed.

8.3 INTERPRETATION OF CAMP OPENNESS REGULATION

As a first step towards better control over the COVID-19 outbreak in the open-system, several experiments were performed with limited camp openness. With limited camp openness, (parts of) the camp environment were closed or partially limited in capacity. Here, three types of camp openness were considered: an unconditional lockdown, a conditional lockdown or no lockdown. For an unconditional lockdown, the camp was fully isolated from the host community and the vicinity market was closed for refugees. For a conditional lockdown, the host community would be partially allowed in the camp and the vicinity market would open with limited capacity. For the interpretation of these experiments, the main approach is to highlight the benefits and implications of this reduction in interactions from a health and economic perspective.

8.3.1 Interpretation of Static Implementation of Limited Camp Openness

A first round of experiments tested the effect of static implementation of lockdowns. Here, the total lockdown would hold on for the total 90 days. To interpret its effect, it is discussed if (partially) closing the camp for people from host communities and its facilities is a good measure to control COVID-19 infections in an open-system refugee camp. The outcomes of limiting camp openness showed a significant effect on both interactions and infections. Firstly, a limited camp openness can be interpreted a highly effective way to control infections. In an open-system, the highest control can be reached with far-reaching limitations on contacts among people and by closing facilities with usually high concentrations of people (i.e.trough an unconditional lockdown). Conditionally lowering capacities for host communities and in-camp facilities would still result in a relative high share of infected people (80%). Therefore, from a health-based perspective, it it relatively most effective to fully limit interactions between refugees and host communities and to close the vicinity market. At the vicinity market most interactions occur for both populations and with highest concentrations of people. Therefore, this location is judged to be a likely source of infections and are therefore a potential source of an outbreak.

However, the downside of this static implementation is highlighted from an economic perspective. Closing the camp environment for host communities causes a halving of the total number of interactions inside the camp. This on itself was an expected outcome, but putting its effect in a broader context highlights some interesting things. Starting with the fact interactions drop by half, a loss of around half of the different economic activities among the two populations is caused. Inside boundaries of the camp and at bigger markets, an approximate 12% and 51% of the total interactions is represented by the participation of host communities. This means, the effect of sticking to an unconditional lockdown could in practice mean to have a very negative effect on economic flourishing activities both population cooperatively work in, suppressing income or livelihood-generating activities. To illustrate that, Filipski et al. [2020] estimates a yearly revenue of 6.000 US dollars for enterprises at the vicinity markets in the Rohingya camps, which in case of an unconditional lockdown for 90 days would drop by 2.000 dollars.

In general, these results imply a weak effect of an unconditional lockdown when focusing on balancing the desired trade-off between infections and (economic) interactions. In other words, a static application of a strict lockdown is effective for reducing infections in the open-system and can be valuable for reducing the risks of spill-overs of transmissions from outside the camp or oppositely. However, this is for high economic costs, as the valuable interactions between refugees and host communities are cut-off. On longer terms, this poses a threat for livelihood-generating activities, which could have far-reaching consequences for the well-being of the Rohingya population.

8.3.2 Interpretation of Dynamic Implementation of Limited Camp Openness

A more balanced way of controlling COVID-19 infections but also sustaining a degree of economic interactions between both populations can be introduced by applying a dynamic implementation of camp openness. From the model results, it was concluded the effectiveness of a dynamic lockdown is as effective for reducing interactions, but can create 60% more economic interactions between refugees and host communities (see table 8.1).

Table 8.1: Effect of static vs. dynamic lockdown

	Economic interactions			Infections	
	Rohingyas	**Host community**	**Reduction**	**Absolute**	**Reduction**
Open camp	15.751	6.752	-	1181	-
Unc. lockdown	12.601	5.132	80%	248	80%
Cond. lockdown	7088	3038	45%	992	16%
Dynamic lockdown	12600,8	5401,6	20%	259	81%

The most important take-away from these model outcomes is the fact that allowing interactions of refugees and host communities can be possible in times where little infections occur. This means, if the camp opens and closes more frequently based on current infections, the impact on limited refugee-host interactions in the camp environment can significantly be reduced. Here, infections can still be controlled and reduced, which makes this type of camp openness a desirable solution from a health and economic perspective. An important practical implication for the interpretation of these results is the fact that this type of camp openness implementation demands a strict and well-informed control over current infection numbers. This requires frequent testing and monitoring of current infections, which is a intensive task in overcrowded camp. Whether this is feasible is out of the scope of this research. Nevertheless, the model results show a first effective step for protecting the interactions between refugees and host communities. Based on static lockdowns, no balance exist for controlling infections and economic interactions, but the dynamic approach clearly shows the potential to better protect the refugee camp economy, resulting from the interactions between refugees and host communities at the economic spots in the camp environment.

8.4 INTERPRETATION VACCINE ALLOCATION STRATEGIES

Five different vaccine allocation strategies were experimented with, with the goal to set a balancing trade-off effect for *infections* and *interactions* in the open-system refugee camp environment. Vaccines usually are a more long-term solution for controlling the spread of an infectious disease, as it sets a basis for long-term group immunity [Grauer et al., 2020]. In this section, the interpretation of implementing different vaccine strategies is given by interpreting the effectiveness of each strategy. The interpretation of effectiveness is determined by weighing three factors which relate to controlling the COVID-19 trajectory in the open camp: (1) keeping control over total infections, (2) reducing health-related risks by lowering severe/critical infections and (3) interpreting the sensitivity for each strategy to vaccine infectiousness. A summary of the results guiding this interpretation is presented in figure 8.6.

8.4.1 Effective Strategies for Controlling COVID-19 Infections in an Open-system Camp

To better control infections inside the camp environment, strategies are compared on their effectiveness on reducing COVID-19 infections. Here, a lower speed of spread and a lower cumulative number of infections as a result of vaccine prioritization is considered desirable, as it is assumed to reflect two benefits. Firstly, lower speed of the development of infections reduces the chance of large outbreaks and therefore lowers the risk of health-related needs for medical assistance (if large shares of a population are

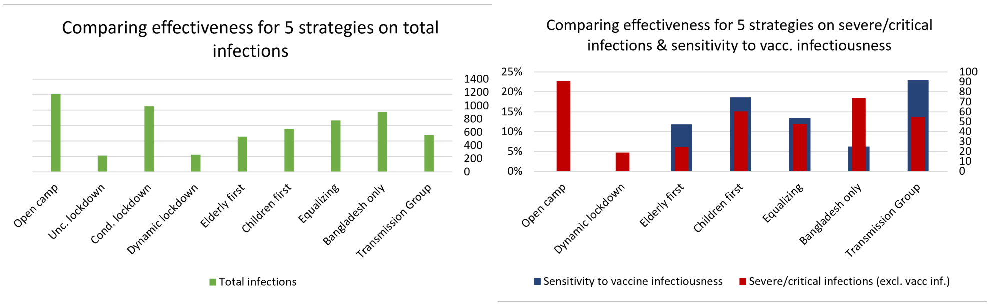
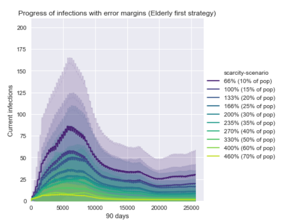


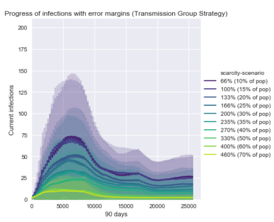
Figure 8.6: Comparing five vaccine allocation strategies on three factors: refugee-host interactions, total infections, severe/critical infections & sensitivity to vaccine infectiousness

infected with symptomatic implications)[Duijzer et al., 2018]. In an open-system refugee camp, this is even more important: inside refugee camps, medical assistance is relatively underdeveloped, and large outbreaks are undesirable. The fact an open-system is studied, reflects the desirability of controlling absolute infections as large outbreaks can cause spillovers to outside. In studies on vaccine supply chains, this is mainly stated for risks of spillovers from one country to another [Duijzer et al., 2018]. This can be scaled to an open-system refugee camp, which risks to be a source of an epidemic outbreak to the host community or reversed.

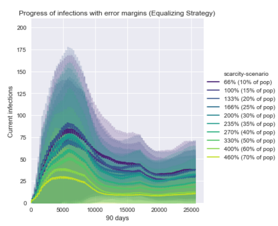
From the model results, the most effective way of controlling infections can be obtained by prioritizing either elderly or transmission groups. As depicted in figure 8.7a & 8.7b, the main difference between these two strategies and other strategies is reflected by its highest reduction of infections in the initial 30 days. Also, cumulative infections can be lowered significantly compared to other studies.



(a) Elderly first



(b) Transmission group



(c) Equalizing

Figure 8.7: Interpretation of controlling infections per strategy

The main reason for the differences between the strategies is interpreted by stressing the importance of two factors. Firstly, an important factor is the level of *availability of vaccines*. This was illustrated by model results for the BO strategy, which excluded Rohingyas from the vaccination program. Here, the low share of vaccinated refugees on the total population in the open-system camp resulted in a high number of infections and an outbreak inside the camp. From a perspective of 'controlling infections' in combination with the context of an open-system refugee camp, this strategy is interpreted undesirable. But also other strategies show the importance of sufficient vaccine availability. When measuring the sensibility of vaccines, an stronger increased control over infections can be measured for a linear increase of vaccines. This can be derived from the different levels of vaccine availability, as shown in figure 8.7.

The second factor deciding effective control over infections in the open-system is related to the factors *susceptibility* and *risk of transmission*. The first factor determines the level of susceptibility to an infectious disease when being exposed to an infected person. In this study, an increased susceptibility was assumed for elderly. The risk of transmission determines the chance of getting infected by or infect other individuals, due to relative high levels of interactions. In this research, this was assumed to yield for adults and children. For both prioritizing elderly (reducing the share of susceptible age-groups) or transmission groups (reducing the share of high-risk transmission age-groups) are effective as these two factors are most prevalent compared to others. The CF strategy is relatively effective as well, but its difference can be explained by the fact children have a lower *susceptibility* to getting infected. The EQ strategy is not effective, as the equal division of vaccinated individuals per age-group causes an under-representation of age-group with a high level of susceptibility (see figure 8.7c).

8.4.2 Effective Strategies for Reducing Health-related Risks for Severe & Critical Infections

From a health-based perspective, strategies are compared on their effectiveness on reducing severe and critically symptomatic infections. Here, a lower share of severe and critical infections is interpreted as a valid counter-argument for judging vaccine allocation strategies on their effectiveness for increasing economic freedom (as discussed in section 8.5.2). Namely, the minimizing of is the conventional aim of effective vaccine allocation strategies Duijzer et al. [2018], and is the most frequently chosen strategy for COVID-19 responses in countries worldwide Matrajt et al. [2020].

To minimize the risks of severe and critical infections, prioritizing elderly is most effective. This is not a surprising result in general, as minimizing health-related risks is closely linked with prioritizing high-risk groups, which are usually elderly. In this research, age-groups elderly and older adults were assumed to have a significantly higher *rate of symptomatic infections*. This explains why the prioritization of elderly (>60 years, followed by older adults (40-60 years), is most effective for reducing severe and critical infections (see red line in figure 8.8).

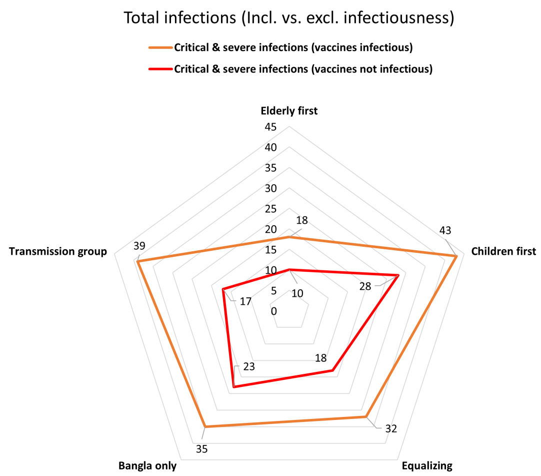


Figure 8.8: Comparing five vaccine allocation strategies on severe & critical infections and infectiousness

A more interesting interpretation through a health-based perspective is the increased difference for the TG strategy and CF strategy if vaccinated individuals are infections (when comparing the red and orange line). Both strategies show to be significantly sensitive to vaccine infectiousness, resulting in a significant higher share of severe/critically infected people. For this, the main reason can be explained by interpreting two factors: the share of vaccinated, high-risk transmission groups (adults & children) and (2) the share of non-vaccinated, high-risk vulnerability groups (elderly). Vaccinating transmission groups and children results in an under-representation of vaccinated high-risk elderly, which are still susceptible and more likely to face a severe/critical infection. This risk is *further increased* if transmission groups are vaccinated first, as their activeness in the camp is high and they can still be infectious. This shows an important difference between the EF strategy and the TG strategy which are both equally effective for total infections, but not for reducing severe and critical infections if vaccines are not high in efficacy. In the model, efficacy of 90% was used, but as vaccine efficacy for COVID-19 vaccines differs per type of vaccine, this could be an implication of the TG strategy.

8.5 INTERPRETATION OF DYNAMICS BETWEEN CAMP OPENNESS & VACCINE ALLOCATION STRATEGIES

The goal of this research is to analyse what strategies exist for an effective trade-off for allowing more refugee-host interactions in an open-system refugee camp on one hand, but controlling COVID-19 infections on the other. In previous sections, both the implementation of camp openness regulation and the allocation of vaccines were interpreted effective strategies in separation. Here, dynamic camp openness by evaluating the current state of infections can be effective, but an implication is its lack of long-term feasibility if economic conditions worsen as a result of limited (economic) interactions. If available, vaccines can be used for the long-term and both types of measures can have a stronger *combined* effect.

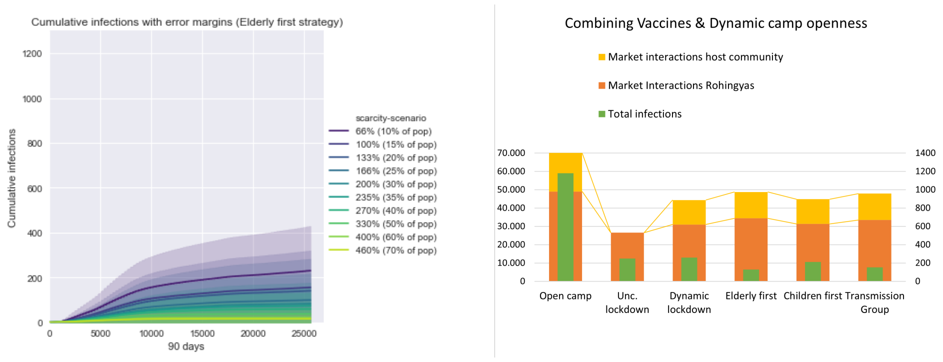
8.5.1 An effective strategy for controlling infections by combining vaccines & limited camp openness

To strengthen the effectiveness of the balancing infections and interactions, results from chapter 7 showed a combined implementation of camp openness regulation and vaccine allocation further allow for more interactive freedom. Translating these results to a broader context, it means an effective strategy for protecting refugee-host interactions *and* controlling COVID-19 infections can best be reached when refugee-host interactions are tolerated in times of low numbers of infections. Here, the model indicates a lower chance of an outbreak, for which the total costs of staying home would not compensate covering the risks of the refugees by keeping everyone home. If infections are low, more interactive freedom can be tolerated while sustaining a guaranteed level of safety. This risk is lowest in combination with higher shares of people vaccinated. In the initial 30 days, only 15% (batch 1) of the people is vaccinated and infection still grow. However, after second batch covering 45% of the people, infections hardly grow. Especially after this phase, more freedom can be allowed.

In general, two main advantages are recognized of combining dynamic camp openness and vaccines. Firstly, from a health-based perspective, further *control* over the COVID-19 outbreak can be achieved (see figure 8.9a). The main difference compared to not vaccinating is the significantly lower speed of spread in the initial 30 days. This is promising, as the base case predicts a potentially large outbreak in this period of time, which can be managed even for low vaccine availability. This is valuable, as from a health-coordinator's perspective controlling the outbreak is really important: for the refugee's health, but also for the risks of spillovers of infections to outside risking the host community's health. Secondly, the combination of vaccines and dynamic camp openness indicates to offer a solution for allowing more public activities. The model outcomes in figure 8.9b show that total infections (for every strategy) are lower, and go hand in hand with sustaining a degree of interactive freedom. From an economic perspective, this is desirable: as infections are controllable, essential public facilities such as markets, schools, mosques and socializing hot-spots can be opened earlier.

8.5.2 An effective strategy for increased refugee-host interactions with an economic focus

The relatively straight-forward and effective combination of dynamic camp openness and vaccines paves the way for interpreting model result through an economic lens. Also, the real benefits from each vaccine allocation strategy were not exploited yet, but do offer an interesting trade-off for allowing more economic freedom. A last model analysis focused on analysing if refugee-host interactions could be more explicitly allowed at the markets, influenced by different vaccine allocation strategies. Here, the



(a) Reduction of infections

(b) Increased interactive freedom

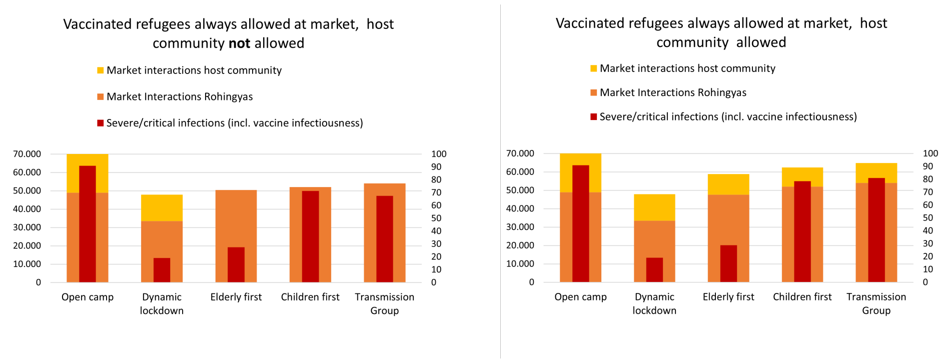
Figure 8.9: Comparing three vaccine allocation strategies in combination with dynamic camp openness: (a) shows the reduction of infections for the Elderly first strategy, (b) shows the reduction of infections per strategy and the cumulative interactions by Rohingyas & host communities

guiding principle was to always allow vaccinated individuals at markets, and compare the strategies on maximizing refugee-host interactions and controlling infections.

For maximizing refugee-host interactions, prioritizing transmission groups is most effective, both including or excluding the host communities (see figure 8.10. Compared to other strategies, this strategy is really effective as the age-groups most actively involved at markets are prioritized for vaccines: adults. From a pure economic perspective, this could be a solution for most effectively sustaining the interactions between refugees and host communities. However, an important implication of implementing this strategy is its relatively high number of severe & critical infections and is most sensitive to vaccine infectiousness. As low-risk age-groups are vaccinated first, high-risk age-groups remain unprotected, which is reflected by symptomatic infections which are almost three times higher compared to vaccinating elderly first. Especially when the host community is allowed in the camp, this increase is significant and is an important risk which need to be considered. This can be explained by the fact the share of vaccinated people who can still infect others are also most active inside the camp. The more interactions are allowed between refugees and host communities, the higher this risk becomes.

This shows the main trade-off for an effective strategy for allowing refugee-host interactions and controlling COVID-19 infections: prioritizing transmission groups and opening the camp for host communities can allow for more interactive freedom, which protects the refugees and host communities from an economic perspective. However, a certain level of serious infections happening as a result should be accepted. An alternative is the prioritization of elderly. This strategy is significantly more beneficial from a health-based perspective, but does not meet the potential of creating most economic freedom.

To narrow the gap for this trade-off between health and economic focused dilemma, an effective strategy is to lower the risks of getting infected for high-risk people (i.e.elderly). In chapter 7.5.3, model results showed further limiting interactive freedom for elderly could reduce the impact of prioritizing transmission groups and allow more economic freedom at markets, as severe and critical infections among elderly are significantly lower. Interpreting this in a broader perspective, this model result shows a more hybrid strategy is possible of combining camp openness and vaccine prioritization can be applied, if both these align in line with their goal. For example, camp openness restrictions do not necessarily have to apply to anyone, but can also be more specified to age-groups. When facilities and the camp stimulates staying-home regulation for high-risk individuals, these facilities can still remain open for transmission groups. Here, camp openness regulation would take away part of the pitfalls of an effective strategy for allowing economic interactions, as it compensates is risks from a health-based perspective.



(a) Host community not allowed

(b) Vaccinated host community allowed

Figure 8.10: Comparing three vaccine allocation strategies in combination with dynamic camp openness: (a) shows the reduction of infections for the Elderly first strategy, (b) shows the reduction of infections per strategy and the cumulative interactions by Rohingyas & host communities

8.6 APPLICATION OF MODEL OUTCOMES TO REAL WORLD ROHINGYA CONTEXT

In previous sections, several (sub)strategies were proposed which follow from insights of the model. However, these results should not be interpreted in isolation, as camp openness regulation and the choice for a vaccine allocation strategy can depend on several contextual choices and/or dependencies. In order to translate the outcomes of this study to a context which is applicable for the Rohingya refugee camps, a more in-depth contextual description and following interpretation is given in this section. Also, to interpret the outcomes from this study, the exploratory nature of this research is stressed which implicates no 'single best' solution exists in case of vaccination programmes and in context of the Rohingyas.

8.6.1 Considering Refugee Behavior for Deciding on Effective Policies

Starting with the the individual behavior of the Rohingyas, it was concluded a positive effect was measured when individual refugees were stimulated to comply with staying-home when being sick and to letting vaccinated household members go to the local markets. But in context of the Rohingyas, one can not simply state or measure compliance or other desired behavior. Many of the things going on inside the refugee camp go unnoticed, as the camp sites are big, (over)crowded and people here live unregistered and go unnoticed for official regulation [Filipski et al., 2020]. Also, a complex factor is the fact not all Rohingyas inside the camps are in favour of being helped with protective measures in context of the governmental COVID-19 response in the camps. This was for example noticed when concluding low willingness to wearing masks, isolate and wash hands more frequently inside the camps after a few months [Government of Bangladesh et al., 2021]. In different studies focusing on how to help the Rohingyas by raising their knowledge about how to become more resilient to hazards and threats conclude the implementation of simple policy interventions is not a simple task, especially related to changes in their structural behavior. As stated by [Bullock et al., 2021, p.14]: *"the language of the primary beneficiaries (the Rohingya) does not have a written script"*. It implies the steering of the Rohingya's desired behavior, which usually demands a broadly supported effort by the people, can be a hard task.

Different branches of literature on the Rohingyas in Bangladesh state the stimulation of desired behavior of Rohingya refugees is hard, for different reasons. For example, Tay et al. [2019] names the ongoing mental challenges which Rohingyas face as a reason. Due to their backgrounds which is characterized by structural conflicts, demanding things from the Rohingyas is not an easy accomplishment for humanitarian aid workers. Also, communication with the Rohingyas by humanitarian aid workers is a structural problem, with means reaching out with help is not always effective. And these complexities were is even further increased since COVID-19 started. During the pandemic, many Rohingyas were faced with exacerbated problems, expressed in many different natures [Islam and Yunus, 2020].

The complex nature of the implementation of policies which relate to a demanded change in the behavior of individuals should be an important factor when weighing a strategy to coordinate the COVID-19 response inside the Rohingya camps. In the paragraphs described above, it becomes evident that demanding things from a refugee population, especially when it considers their individual freedom, should be carefully weighed. The people cannot be simply demanded to isolate in case of getting sick, especially when their needs are dependent on other things which do not necessarily relate to COVID-19. Also, it stresses the importance of a more long-term solution which can release the burden of social measures, structural exclusion of the camps and limited freedom to sustain a living. This long-term solution is related to the introduction of vaccines, which is discussed more briefly in section 8.6.3

8.6.2 Contextual complexity of coordinating camp openness regulation

A second more contextual interpretation relates to dynamic camp regulation, which was concluded to have a positive effect on the number of infections. By the (partially) limiting of contacts between Rohingyas and host communities and lowering shared facility capacities, a desired drop of infections was registered. However, also the practical regulation of camp openness and regulations of capacities at shared facilities inside the camps is not easy as well. Regarding the limited capacities of facilities inside the camps, no strict rules exist and practical implementation is not very effective as stated during the expert discussions during the model validation. For example, the limiting of numbers of people at shared facilities is really hard to control, except for for formal facilities such as mosques. *"We can only tell the Rohingyas to come to food collection points in small groups. Here, Rohingyas would listen and keep their distance, but on the way back home they would cluster again, with all their friends and families"*, as one of the experts mentioned during these conversations.

And also controlling camp openness is shown to be hard. Since the outbreak of the pandemic, the Bangladesh Government built fences around the Rohingya camp boundaries, as a means to control the number of in and outgoing contacts between the Rohingyas and host communities [IDC, 2020]. Next to that, formal check-points were raised at camp entrances and existing check-points were guarded more strictly. But when really comparing these intended measures to regulate camp openness to its practice in reality, not a one-on-one translation from these intentions to reality can be recognized. From discussions with different experts, the camp fences were built, but not strictly controlled. Also, entering and leaving the camp environment was not as strict, except during the strict lockdown which was imposed in May 2020. During that time, refugee-host interactions were estimated to be cut by around 80%, but since that time mobility almost came back to normal [Ullah et al., 2020]. This is due to the fact regulation of movements from outside to and out of the camp environment is not easy to strictly regulate. And this effect is increased by the fact for many Rohingyas the benefits of staying home do not anymore outweigh the costs of risking to get infected by COVID-19. Last months, the measures stimulating the limiting of people's contacts with others lost effectiveness, which is due to the fact other risks than COVID-19 are lurking their existence, such as hunger a lack of livelihood-generating resources or other basic services [Ullah et al., 2020; Islam and Yunus, 2020; Banik et al., 2020].

These above described paragraphs imply the effectiveness of camp openness regulation depends on either a more strict control or a further extension of building fences around the camps to block undesired movements of people entering and leaving the camp. But it is the question whether this is a desirable direction, both valued ethically and if it is a feasible thing to accomplish. Maintaining intensive control in the camps is hard, and financial and man-power based factors also play an important role.

Therefore, also the regulation of camp openness and the structural lowering of movements of people and their interactions in and around the Rohingya camps seems like a solution which is only preservable on relative short terms. For example, this can already be illustrated by comparing the growth of infections in June 2020 (after which a strict lockdown was imposed for the camps) and for June 2021 (in which the camp is partially open for visitors) in figure 8.11. As the figure and the above described paragraphs indicate, also a more long-term and contextual solution is demanded when studying the practical implications for limiting camp openness.

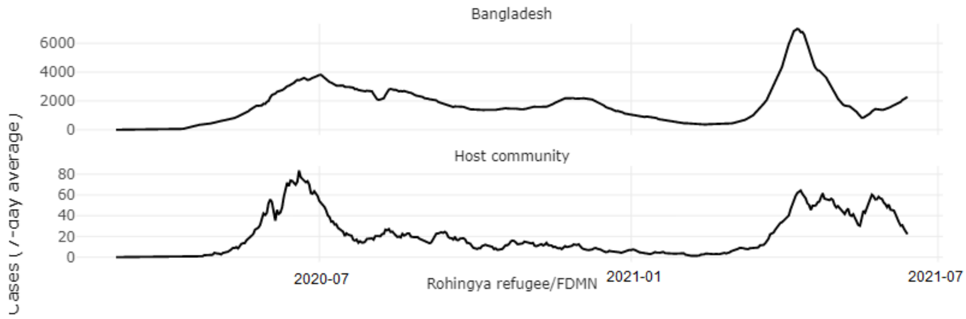


Figure 8.11: Total cases registered in Bangladesh & in the Rohingya camps (2020/06 - 2021/06)

8.6.3 Complex coordination demands for vaccines as a long-term solution

Although the stimulation of health-related behavior and the implementation of contact-reducing policy measures seem effective for the prevention of COVID-19 transmissions, previous sections highlight the complexity of realizing this in context of the Rohingya camps. Not only does it require a structural change of behavior by the Rohingyas in already extremely hard conditions, it is also the question how long policies and changes in structural behavior can be maintained. But with the rapid development of COVID-19 vaccines are now a faster and more long-term solution can now be offered, which can reduce the pressure on the living conditions of the Rohingyas. As discussed briefly throughout this research, different vaccine allocation strategies showed to have a desired effect on creating more freedom to interaction whilst keeping the numbers of infections low. Also, the inclusion of Rohingyas in the vaccine allocation strategy in Bangladesh seems inevitable based on these criteria for both the Rohingyas themselves as for the hosting communities. But for the implementation of a vaccine allocation strategy as well, more contextual insights are needed.

When purely studying the outcomes in this research, it seems most obvious to pick the EF strategy or TG strategy, depending on the intention to either minimize health-related complications or create maximum economic freedom. However, deciding on a vaccine allocation strategy is also a more complex task than simply weighing its effectiveness expressed in interactions and infections. Namely, picking a vaccine allocation strategy is not only a matter of weighing different trade-off between infections and refugee-host interactions. In general, the nature of allocation problems for scarce vaccines such as for COVID-19 is the crucial ethical values which need to be considered and the following dilemmas between conflicting objectives [Keeling and Shattock, 2012]. In this study, economic values were considered an important aspect of vaccine allocation strategies, as its effectiveness was partially expressed as an economic outcome of interactive freedom for both Rohingyas and host communities. However, one could argue to always prioritize a health-focused perspective, as this is ethically the most right thing to do, and are also the fundamental basis of economic protection as stated by Duijzer et al. [2018]. In this research, these ethical values were not considered unimportant, but the aim was to shed a light on the economic opportunities which come with different vaccine allocation strategies.

Also, vaccine allocation strategies should be valued in a broad context. Namely, vaccine allocation takes part of a total vaccine supply chain, and cannot be considered apart. Other factors which should be kept in mind choosing a vaccine allocation strategy are characteristics like its effectiveness per doses, the frequency of injecting the people for effective vaccination, the possibilities to reach out to the people intended to vaccinate and the willingness of people to get vaccinated [Duijzer et al., 2018; Chopra and Meindl, 2007]. To illustrate this in line with the Rohingyas, previous vaccination programs showed it was hard to socially mobilize Rohingyas through vaccine campaigns during the 2017–2018 diphtheria outbreak, for religious reasons and influenced by mistrust, misleading information and safety concerns [Jalloh et al., 2020]. Also during this COVID-19 crisis, cultural factors play a role influencing the Rohingya's decisions. For example, elderly Rohingyas tend to have bigger concerns with the injection of multiple vaccines for religious reason, which could complicate a vaccine allocation strategy such as the EF strategy.

The paragraphs as described above raise the question on how to then interpret the results from this study. Here, is it most important to consider two main things when translating the outcomes of this study into practice: (a) by keeping in mind the context-related factors as described above and (b) the exploratory nature of this research. Regarding point (b), it should be clear it is not intended to propose a single best solution for a vaccine allocation strategy. Namely, the model which was used in this research exists of different parameters, of which some have broad parameter spaces. Therefore, parameter spaces which follow from the analyses do not lend well for offering an single best or optimal solution. What the outcomes do show is a good indication of how the model of study performs: what vaccines allocation strategies have a higher effectiveness overall, related to the main KPIs and how these balance each other.

8.7 CONCLUSION

Chapter 8 presented a model validation and an interpretation of the model outcomes. For model validation, a sensitivity analysis, literature comparison and an expert interview were carried out. The sensitivity analysis showed the model of study is mainly sensitive to the average force of transmission and the time of being sick, which is mainly affecting the number of infections. The number of interactions was a more robust component in the model under the variation of these sensitivity parameters. From the literature comparison, it could be concluded a valid COVID-19 transmission model was implemented, but with a potential overestimation of the number of infections. Based on other studies on non-vaccine-related topics, outcomes of this study indicate a high validity for the effect of wearing mask and stay-at-home compliance. Regarding camp openness, considering an unconditional lockdown was a valid theoretical choice (based on other studies with similar results), but less valid for real-world comparison as concluded from expert interviews. For vaccine allocation strategies, a high validity was concluded for the two well-performing strategies which prioritize elderly and transmission groups over other groups. For other strategies, outcomes were more conflicting with other research. Model results from previous chapters were interpreted as well. From these model outcomes, it can be concluded the most effective measures for creating a balance between infections and refugee-host interactions are to implement a combination of vaccine and non-vaccine related measures and other incentives triggering lower infections. Here, dynamic camp openness regulation, stimulate stay-at-home measures for infected individuals and prioritization of elderly (starting with elderly people and ending with children) or transmission groups (older adults first from 40-60 years, then younger adults from 18-40 years, with elderly above 60 years and children under 18 years in later stages) show most promising results. However, a main take away is to also consider contextual variables other than model results, as the implementation of these measures is highly contextual for the Rohingya camps.

9 DISCUSSION

In chapter 9, the model and its outcomes, validity and interpretation are discussed. In section 9.1, a discussion on the model sub-concepts and the integrated model concept and their underlying assumptions and simplifications is given. Section 9.2 discusses the validity and the outcomes of this study, which result from the model. Here, the model validity is reflected upon and what implications exist for the interpretation of results and translating these to the context of the Rohingyas. Lastly, section 9.4 concludes.

9.1 DISCUSSION OF MODEL SUB-CONCEPTS, SIMPLIFICATIONS & ASSUMPTIONS

For the construction of the model and its underlying concept, several assumptions and simplifications were made. For each sub-concept and its formalization, arguable choices were made which could have had an effect on the model and its results. To reflect upon this, a selection of assumptions and simplifications which are made to create these sub-concepts and the integrated concepts and the following implications and limitations are discussed.

9.1.1 Limitations for Sub-concept 1: refugee-host interactions

Refugee-host interactions were conceptualized and formalized by determining daily activity schedules for each Rohingya household and each individual from host communities. Driven by these daily schedules, interactions were a result at three types of places: in-camp facilities, in-camp markets and the vicinity market. But differentiating these interactions over only three types of activities is not a realistic representation of the Rohingya context: in practice, Rohingyas visit various places, such as learning centres, schools, mosques, water & food facilities and social zones. The implication of only assuming three types of activities is the fact that different risks of infections at different places are only depending on how long one spends here, not on other characteristics such as a facility specific contact rate or whether an facility only allows limited numbers of people or not. For example, a difference which is not measured in this study is the fact learning centres are more strictly regulated than visiting one of the water & sanitation facilities.

The choice to only model three types of activities was made for decreasing the computational power which was needed for the model to run. In making this choice, it was the main aim to keep ratios of Rohingyas and Bangladeshi visiting certain places intact, as this was the main intention on how to model the transmission process between Rohingyas and the host communities entering the camp environment. As this ratio was still intact by only considering two types of interactive activities, the main focus of this study was not affected by this choice. Also, different lengths of duration when visiting shared facilities were used, which represent differences among spending times for different activities.

A second implication regarding the simplified concept for refugee-host interactions relates to the fact shared facilities are assumed to concentrate around geographical spaces. This is true for food & water collection points, but is not true when considering the practical process of visiting in-camp markets. Visiting in-camp markets is not only the process of interaction in small, static shops. In the Rohingya camps, a lot of trading and dynamic, temporary facilities are created every day. This means, interactions in practice are much more geographically spread, especially informal interactions between the Rohingyas and Bangladeshi. In the model, an implication this assumption therefore holds is a potential overestimation of the numbers of infections at in-camp facilities.

A third limitation regarding this concept is the fact it assumes no contacts among people at home. In and around the shelters, Rohingyas usually interact with their neighbours, which also sets a potential basis for infections. However, this model only assumed the risk of getting infected at home by a sick household member. Regarding this assumption, a potential underestimation of infections at home is expected.

A fourth and last limitation in this sub-concept is the assumption of interactions as a result of Rohingyas meeting other Rohingyas from their sub-block in the Nayapara RC environment or by meeting a local Bangladeshi. But in practice, camp boundaries are vague and differences between sub-blocks are only formal. As no data on cross-camp movements can be obtained and validated, it is hard to estimate social mixing patterns among Rohingyas from different sub-blocks. However, an isolated structure of the infrastructure for each sub-block is not a valid assumption, which indicates more cross-camp interactions. Therefore, the number of interactions might be a limited representation of reality, which potentially lead to an underestimation of the number of infections among Rohingyas. This underestimation is aimed to be compensated with random infections, which are assumed to happen on a daily basis as well.

9.1.2 Limitations for Sub-concept 2: COVID-19 transmissions

Regarding the COVID-19 transmission model, three main assumed were arguable.

A first assumption which is considered a potential lack of this research is the indifference of infectiousness of individuals with different types of infections. In this research, asymptomatic and severely individuals were assumed to be equally infectious to susceptible people. However, several studies point towards the fact that symptomatic infections are more infectious to others. For example, infecting others is more likely as a result of coughing & sneezing, as was concluded by Stadnytskyi et al. [2021]. The implication for this assumption can be translated to two shortcomings in this research: it underestimates the infection-trajectory if *no* vaccines are applied. Namely, a higher share of people is infected with symptomatic consequences. Furthermore, it *overestimates* infectiousness of vaccinated individuals. Namely, vaccinated individuals can still be infected, but always results in an asymptomatic infection. Therefore, following the insights from Stadnytskyi et al. [2021]'s research, infections from vaccinated people would be less significant.

Furthermore, the process of both *risking and getting infected* was simplified in this research. Here, an increasing chance of getting infected was assumed for spending a longer time with an infected person up to 15 minutes, which after 15 minutes would result in an insurmountable infection. Although this time-based and aforementioned demography-based factors influencing the transmission process can be validated with existing literature, other factors are left out of scope. For example, gender-specific transmission processes differ [Metelmann et al., 2021], indoor and outdoor transmission processes or most likely different [Habeebullah et al., 2021], face-to-face contacts increase the chance of transmission [Chen et al., 2021] and symptomatic infections are also contribute more to infecting others [Vermund and Pitzer, 2021]. These assumed simplifications of the transmission process do not necessarily mean an implication for this research, but could still be an influencing factor in combination with studying the effectiveness of vaccines. This is discussed in section 9.1.3 more briefly.

A last critical assumption for the COVID-19 transmission process is its assumption of re-infectiousness. In the model, a minimum time of becoming re-infectious was set to 2 months, but according to literature this is an uncertain and therefore weak assumption. In most recent studies, which could not be consulted at the time of constructing the model, a minimum of three, six and seven months is estimated by Torres et al. [2020], Stokel-Walker [2021] and West et al. [2021] respectively. In the model, a two month period is an underestimation, which might have had lead to an overestimation of infections.

9.1.3 Limitations for Sub-concept 3: Vaccine Allocation Strategies

Five vaccine allocation strategies were tested, which prioritized the allocation of vaccines over different age-groups. Although differentiation over age-groups is a common allocation approach [Duijzer et al., 2018], it holds some practical implications related to COVID-19. First of all, many COVID-19 vaccine allocation strategies firstly prioritize healthcare and other essential workers. For example, this was initiated in the first version of the Bangladesh NDVP (see appendix C.3). This was not included in the model, which potentially overestimates the number of vaccines available for the first priority group in the first batch of vaccines: the number of healthcare & essential workers in the Rohingya camps is estimated to represent 10% of the total Rohingya population in the camps. On the other hand, it is questionable whether the fraction of healthcare workers receiving a first vaccines is big enough to influence this result which was also concluded for the relatively small group of elderly (representing 5%) in the camp.

A second simplification which potentially influences model results relates to the total vaccine supply chain, which consists of the four inter-related phases: (1) production, (2) characteristics, (3) allocation and (4) distribution of the vaccines [Duijzer et al., 2018]. Here, only phase 3 was explicitly modeled, but phase 1, 2 and 4 were simplified: production of vaccines was not mentioned, and only one injection was assumed to be effective for 90% efficacy. These assumptions are arguable, as no currently developed vaccine meets these criteria. Namely, most of COVID-19 vaccines request a double injection over multiple weeks, which potentially lead to an overestimation of vaccine effectiveness. Namely, if the number of vaccines per person needed would double (for two injections), vaccine availability would face far more scarcity. Regarding phase 4, the assumption of immediate distribution of vaccines after they become available is not a likely scenario. As the infrastructure and geographical structure of the Rohingya camp do not always lend themselves well for setting up efficient health-care facilities Jeffries et al. [2021], it is more accurate to consider at least some days of delay in the delivery of vaccines.

A last significant assumption which is expected to limit some of the model results is the assumption of 100% show-up for vaccines by Rohingyas and Bangladeshi. Although no current literature can approve the fact this assumption can be fully ruled out, there are some indications which point towards challenges in increasing the willingness to get vaccinated in Bangladesh and in the Rohingya camps. For example, McGowan et al. [2020] sums up most important factors in context of the Rohingyas which hold many Rohingyas back from making use of testing facilities: high levels of fear, the belief that COVID-19 does not exist, the belief that God will prevent them from getting infected and not getting permission by a family member. Although these factors do not need to be necessarily true for getting a vaccine, these factors indicate a 100% show-up is an overestimation in this research, overestimating the absolute effectiveness of the vaccine allocation strategies in general.

9.1.4 Limitations for Sub-concept 4: Camp Openness Regulation

Camp openness regulation was based on the assumption of evaluation of the basic reproduction number $R0$, a non-forecasting indication of the infection growth. Considering $R0$ is not a implication for evaluating an infectious disease, but it is a very simplified version of the effective reproduction number $R\epsilon$, which also makes use of forecasting and estimates the likeliness of future infections [Mahase, 2020].

Although it is not clearly indicated what method is used to impose movement restricting measures inside the Rohingya camps, the evaluation of $R0$ is most evident. Namely, the number of growing infections were used to also increase strictness of in-camp facility capacities, according to the experts in discussions. However, what the evaluation of $R0$

still implies is the assumption of having full knowledge on current infection numbers. In other words, the assumption implies full testing capacity is available and is used. Although testing has increased in the last months, the assumption of full knowledge on infected individuals is unlikely. For this, the indicators for not wanting to get tested named in previous section are main reasons. Another reason is the fact asymptomatic infections can go unnoticed by people, who then not even consider testing. Therefore, $R0$ evaluation might have had a more effective influence on reducing infections by opening and closing the camp. Namely, the model assumed a high $R0$ was the main factor to close the camp from visitors. As discussed in this paragraph, this $R0$ might be an insufficiently valid representation of reality.

9.1.5 Limitations for the Integrated Model Concept

The integrated model concept which is a combination of the four sub-concepts was also based on some arguable assumptions and simplifications. One of the most arguable simplifications of this integrated concept is the assumption of the fact *interacting with others* causes livelihood-generation for individuals. This means, it is assumed the only source of livelihood generation is achievable when refugees leaving their tent by attending or visiting public facilities such as the vicinity market and the in-camp facilities. This assumption was made to simplify the mechanism of both livelihood-generating activities and setting a basis for a transmission model which is activated when individuals interact. However, this might not be a completely valid representation of the big set of options for refugees to generate and gather live saving essentials. For example, Rohingyas are very community-oriented. As every sub-block is lead by so-called *Mahjis*, it is not unrealistic the people cooperate with each other more to generate sufficient levels of livelihoods, but at the same time limiting their contacts with others.

A second more general limitation which relates to the integrated concept is the simplified link of being compliant to measures by individuals and other concepts in the model. Compliance is assumed to be a result from *knowing to be infected* and the *willingness to comply*. However, willingness to comply was modeled as a random factor, which in reality is a much more complex mechanism. For example, increased social fear as a result of tightened rules and measures or decreased social fear as a result of higher numbers of vaccinated people are likely factors to also influence the willingness to comply. Another factor could be the number of days not having visited the markets for accessing food or water could be an influencing factor for levels of compliance.

These arguments show the links between the four integrated concepts are a simple representation of reality, which potentially affects the model outcomes in this study. In general, these implications reflect the complexity of fully covering all important aspects which can be recognized as important contextual and valid structures of a refugee camp. The fact not every model structure is modeled without implications does not imply the model is not useful. However, context-specific model structures and simplifications discussed in this section should be carefully weighed by decision-makers.

9.1.6 Limitations for Model Resolution & Experimental Design

Besides limitations reflected in conceptual choices, also some limitations exist regarding the model resolution, both defined over time and space. Regarding the resolution of time, a limitation of the model is the fact both high-resolution mechanisms were combined with low resolution mechanisms. For example, a high resolution mechanism which is studied is the transmission process of infections, which are measured every 5 minutes as a minimal time step in this model. To study relatively long-term effects of vaccines, 90 days are studied which is a more low resolution level over time. The implication for this study this combination entails is the fact the model is computationally intensive. Therefore, in combination with a lack of time to perform this study, running various different experiments was limited. Therefore, an important implication for this research is the potential non-researched scenario space, which might lead to an underestimation of potential insights which back the model outcomes. To generate robust outcomes from a model, many different model runs are needed and should be varied with over large parameter grids. Due to a lack of time and the model's intensive computational demands, this could not fully be achieved. Running experiments was based on two and three-level fractional experimentation designs, whereas a *Latin Hypercube Sampling* or *Monte Carlo* design for experimentation would have increased the knowledge of total solution spaces for different vaccine allocation strategies and for other parameters in the model [Van Dam et al., 2012; Wu and Hamada, 2011]. To cover a higher solution space, a different program could have been used to generate more model results. The model was run in *Netlogo*, but more advanced languages for running ABM models exist, such as MESA which can be used to more efficiently run and analyse these models trough modular components.

A second limitation which follows from the implication from previous paragraph, is the fact some mechanisms had to be simplified to reduce the computational power of the model. For example, various types of interactions were aggregated to two types of interactions: in-camp interactions and interactions at the vicinity market. This was reflected upon earlier in section 9.1.1. But what it means, is some value on high resolution mechanisms in the model was lost during the modeling process and it is a subjective matter whether it is desirable both resolutions are chosen in this research as also insights are gained on both ends of the temporal spectrum which is used in this study.

Regarding geographical resolution, a main limitation in this research is reflected by the fact only a fraction of the Nayapara RC camp has been picked for modeling (see figure 3.1). To create high resolution in the model by studying individual refugees and their shelters, ABM does not lend itself well for the modeling of many individual agents which can make the model too computationally intensive. The more practical implication of only studying a smaller fraction of the Nayapara RC camp environment, is the implicit assumption of a fully isolated geographical environment. Namely, the only interactions were modeled between Rohingyas living in this area and the host communities they interact with. But in reality, much more interactions are likely to happen with people from outside the defined geographical area of study.

9.2 Discussion of model outcomes & validity

In chapter 8, model outcomes were validated and interpreted. To reflect on this validation and to translate this judgement into practical advises in this study, the strengths and limitations are discussed here based on the validation process. Here, it should be mentioned these judgements are subjective and arguable. The main aim of this section is to set a basis for further judgement by decision-makers on the validity and therefore applicability of the model outcomes in this research.

9.2.1 Judgement on validation-based strengths of this study

With different validation methods, some strengths came forward for this study which are judged as a valid representation of the real-world system which was studied. One of these strengths which raises the validity of this study is its similarities with other studies on related topics. For example, the conclusion from the sensitivity analysis was similar with other studies on different sensitive model parameters. This means, parts of the model structure in this research are designed similar to other studies with the same focus, and therefore perform similar model behavior which raises the confidence of the model outcomes in this study. Also, when comparing the model outcomes with literature studies on related topics, outcomes can be judged valuable. For example, other studies on COVID-19 and its spread in contexts of refugee camps show the same trajectory over time and with similar outcomes. A second strong similarity is importance of a combined implementation of non-pharmaceutical measures with vaccine-related measures. Measures and effects which were studied related to vaccines and to other measures were judged similarly like other studies, such as the importance of staying-home compliance, dynamic camp openness regulations and fast vaccine roll-outs.

As model outcomes can be compared with other academic literature, this study is judged to have a relatively strong validity for theoretical studying and estimating of certain model structures and policy measures. This means, the exploratory outcomes of the model outcomes are relatively insightful from a theoretical viewpoint. Whether model outcomes are also insightful more practically, is discussed in next section.

9.2.2 Judgement on validation-based limitations of this study

Some model outcomes could not (easily) be classified a valid representation of reality. What this study mainly lacks validity, is translating highly contextual characteristics to model components which can produce meaningful insights which reflect the Rohingya camp context reality. Namely, a main conclusion which was drawn from discussion with experts was the fact some components of the model are hard to validate. For example, estimating the different numbers, types and the duration of refugee-host interactions and validly integrating these into the model is not easy to validate. Reflecting on this uncertainty, more different experiments could have been conducted with variations in refugee-host interactions over the named characteristics. Namely, this could give more insights in the scenario-space of infections resulting from these interactions. Another contextual limitation as derived from the validation process, is the influence of camp openness on the number of interactions and therefore its influence on infections. Three types of lockdowns were considered a driving factor for interactions, but discussions with expert pointed out the ineffectiveness of regulating people's movements inside the Rohingya camps. Based on these insights, a clear gap exists between the intention of policy measures, rules and desired behavior of individuals on one hand, and its practical application to reality. Therefore, a first judgement regarding the validity of this model is the fact it is of a more theoretical basis. To implement insights from this study, one should also really consider other, contextual factors which have not been included in this study.

A second, more obvious judgement on the validity of this study links to its exploratory nature. This study dives into a knowledge gap which focuses on the dynamics between relatively new and non-researched topics, namely vaccine allocation strategies, infections and refugee-host interactions in an open-system refugee camp. For both expert validation and literature comparisons as validating methods it was only possible to consult and compare insights from experts and other literature on related topics separately. The validation of these integrated dynamics is hard and sometimes not possible. For example, a well-known validation technique is historic replay, which is a validation methods where historical trends on related topics are studied. As COVID-19 is a relatively new topic, using validation techniques as such was not possible, which still leaves a significant interpretative space on the interpretation and robustness of the dynamics between the three topics. On the other hand, not being able to fully validate these non-researched dynamics on relatively new topics does add value to the scientific contribution. This scientific contribution is discussed more detailed in the next chapter.

9.3 DISCUSSION ON REAL-WORLD APPLICATION & IMPLEMENTATION OF MODEL OUTCOMES

Previous sections highlighted several limitations and judgements on the conceptual model, assumptions on which this model was created and the validity of the outcomes generated by this model. Here, most general conclusions which were drawn stressed the fact both the model structure and its outcomes were a simplified and mostly theoretical basis of the real-world context of the Rohingyas. To construct the model, many assumptions and simplifications were made to capture complex sub-concepts of study. And the complexity of these sub-concepts was increased even further as these were combined. This combination of sub-concepts allowed for studying the dynamics between these, which performed the insights as discussed. But the combination of these sub-concepts also implies outcomes in this study are highly subjective for interpretation. As the model was constructed with many different variables, relatively new (combinations of) concepts and are aimed to represent a highly contextual system, the outcomes in this study should not be interpreted as 'single best' solutions. This means, this study does not advise to implement the 'elderly first' strategy for example, as it performs best on creating a trade-off for the most interactive freedom whilst keeping low infections. Also, it does not advice to provide a set of different measures which is found to be a most effective combination to reach the same trade-off. As context-dependency was judged a very important factor for effective coordination of the COVID-19 response in the Rohingya camps, which could not all be captured in one model, this study does not claim to provide highly valid and applicable real-world solutions.

But what this study does show, is a good indication of several effects which were measured. Due to the exploratory nature of the model, insights on the direction and weight of these effects can be used to judge a final implementation of a policy in real-world application to the case of the Rohingyas. To give an example, one of the model outcomes indicated a positive relation between the combination of non-vaccine and vaccine-related measures and behavior. Namely, staying-home measures and a dynamic policy for camp openness in combination with the introduction of vaccines showed most positive effects on the KPIs *infections* and *refugee-host interactions*. Here, one could not simply state the 'elderly first' strategy is more effective than the 'Bangladesh only' strategy because as after a period of 90 days infections were 45% lower with the same number of interactions. But what *can* be stated is the significant difference which can be recognized between the two strategies. As various model simulations were performed to measure different effects, it is possible to give an indication between the statistical differences between two or more effects. This allows for comparing different strategies with each other, and judge them on their desired direction, which is still a subjective, ethical task for a decision-maker.

Overall, model outcomes in this study can be used as an academic support for real-world application in context of the Rohingyas and the COVID-19 response. As introduced in chapter 1, the Government of Bangladesh raised a document with initial operational guidelines on their COVID-19 vaccination program in Bangladesh. Although these guidelines suggest to include the Rohingya population in their vaccine programmes, and several guidelines are set-up for the allocation of vaccines in Bangladesh, this study creates an academic basis to support these guidelines. For example, to include the Rohingya population in the national vaccination program is supported by insights from this study, as exclusion of Rohingyas in the vaccination programs showed significant different results compared to including them. This study also gives room to reconsider decisions which were made to create the operational guidelines. As the delivery and allocation of vaccines in Bangladesh is characterized by different challenges and hurdles, academic insights like from this study can be used to change and further improve the vaccination programmes.

9.4 CONCLUSION

This chapter discussed and reflected upon the model which was used in this research and the outcomes which were generated. Firstly, the limitations for sub-concepts and their integration to construct this model were discussed, based on several model assumptions and simplifications. Also, limitations were discussed for choices made deciding on the model's resolution on both time and space. Secondly, model outcomes were discussed, based on the validation in chapter 8. Here, a judgement was given on the strengths and limitations of these outcomes. Thirdly, insights from previous sections were used to discuss the real-world application of the model outcomes and apply these to the context of the Rohingyas.

The main limitations in this study as addressed in this chapter are:

- Related to different sub-concepts, is the high number of simplifications and assumptions which were used to integrate and model these.
- Related to the integration of different sub-concepts is the simplification of links between these concepts and complex mechanisms can be judged as oversimplified.
- The combination of high resolution and long-term focus on the total period of time studied. As both are included in the model, computationally intensive processes needed to be simplified and are therefore less accurate.
- Related to this study's validity is the inability to validate (the combined effect of) relatively new and non-researched concepts.
- Related to the real-world application of model outcomes is the inability of the model to capture all aspects of the highly contextual case study of the Rohingyas.

General strengths of this study are:

- High validity when comparing model results with other studies.
- A high level of resolution for complex mechanisms in combination with a relatively long period of studying, which allows for studying short and longer-term effects.
- An academic support of decision-making on the COVID-19 vaccine response in Bangladesh, with a specific focus on the Rohingyas.

10 CONCLUSIONS & RECOMMENDATIONS

In chapter 10, the research questions are answered with the findings from this research. Firstly, the sub-questions which were analysed and answered in section 10.1. Secondly, the main research question is answered in section 10.2. With these answers, recommendations to improve the COVID-19 response in context of the Rohingya refugees in Bangladesh is given in section 10.3. Thirdly, the scientific contribution of this research is presented in section 10.4 and recommendations for further research in section 10.5.

10.1 ANSWERING THE RESEARCH SUB-QUESTIONS

10.1.1 Sub-question 1

What drives interactions in an open-system refugee camp settlement, influenced by restricting COVID-19 measures?

Sub-question 1 was answered in chapter 2, with an extensive literature study, supplemented with insights from information from desk research and interviews with experts. Here, the goal was to set a basis for grasping how, when and where interactions take place between Rohingya refugees and host communities. Refugee-host interactions were defined as the legal, social and economic interactions which take place between both a refugee population and a host community population, in a refugee camp or outside its boundaries. In this research, interactions are assumed a simplified basis for economic activity, a source of income and livelihood-generation. Also, these interactions set the main basis of contacts between individuals, which is used to study the spread of COVID-19 in an open-system refugee camp.

Answering the first part of this sub-question, the main drivers of refugee-host interactions can be characterized through a certain *type* and *location* of an interactive activity, a *ratio of refugees and host communities* participating and a certain *type of interaction*. In context of the Rohingyas, most frequent types and locations of economic activities are informal interaction (such as trading, selling or small exchanges of services) which take place roughly two locations: at vicinity markets and at smaller in-camp *meeting-points*. The ratio of Rohingyas and host communities at vicinity markets is relatively equal (49-51%), whereas Rohingyas are predominant at in-camp meeting-points (88-12%). Lastly, a the type of interaction which is a mix of meeting each other for buying and selling, going to markets and also a small fraction of labouring exchange can be concluded.

Regarding the second part of this sub-question, the influence of restricting COVID-19 measures was studied as a negative effect on the possibility or willingness to interact. Restricting measures could be categorized in roughly two types: *camp openness*, *in-camp movement restrictions* and *(partial) shut-downs of in-camp facilities*. Here, camp openness was judged a factor to influence refugee-host interactions, as it isolated the camp. In-camp movement restrictions were mainly linked to general rules inside the camp deciding *who* could leave their shelters (i.e. everyone versus only vaccinated people). Shut-downs of in-camp facilities were related to limited openness of in-camp facilities.

Lastly, willingness to interact was judged a factor related to compliance with the measures from previous paragraph. Here, compliance was defined as the willingness of an individual to (not) comply to stay-at-home if infected, wear a mask in public or both.

10.1.2 Sub-question 2

How can different vaccine allocation strategies be defined in context of a refugee camp settlement?

Sub-question 2 was answered with an extensive literature on vaccine allocation. Also, a review of current practices of vaccine allocation initiatives in Bangladesh and Lebanon was used. This question was answered in chapter **??**, with the aim to create a theoretical basis for defining vaccine allocation strategies, and to translate these to a context of the Rohingya refugee camps. Vaccine allocation strategies can be defined as a decision-making process of deciding whom to vaccinate first. It was concluded, two main factors drive this decision in context of COVID-19: the level of *vaccine scarcity* and the *chosen approach for picking an allocation strategy, guided by an objective*.

Vaccine scarcity is high in Bangladesh, as vaccines are expected to arrive in three different batches throughout 2021. High levels of scarcity stress a careful weighing of an approach for vaccine prioritization. Roughly, two approaches exist: (1) a geography-based approach and (2) a demography-based approach. This research focused on the latter approach, as geography-based allocation is judged to be effective for relatively small and isolated systems [Duijzer et al., 2018]. This does not apply to the Rohingya camps, which host many people and are a potential source of infection spillovers to the hosting community or vice versa. A demography-based approach is judged most feasible when prioritizing different age-groups. Namely, age is a relatively easy categorization of refugees; other categorizations are harder to estimate due to the chaotic nature of the camp.

Through this approach, five vaccine allocation strategies were concluded: (1) an 'elderly first' strategy, (2) a 'children first' strategy, (3) an 'equalizing' strategy, (4) a 'Bangladesh only' strategy and a (5) 'transmission group' strategy. In the first two strategies, either elderly or children are prioritized, based on age. Prioritizing elderly can have positive effects for reducing deadly infections and children are judged a potential source of infection to their parents. Through the 'equalizing' strategy, it is tested whether creating equal access of vaccines is desirable, as it allows for judging whether it is effective to distribute vaccines over households, rather than over age-groups. The 'Bangladesh only' strategy highlights the effect of excluding the Rohingya refugees from the Bangladesh vaccination program. Lastly, the 'transmission group' strategy focuses on highly transmitting groups, to see whether this affects the speed of spread.

10.1.3 Sub-question 3

How can interactions in an open-system refugee camp settlement, vaccine allocation strategies and being vaccinated to COVID-19 be conceptualized and formalized in line with an existing infectious disease (SEIR) model?

Sub-question 3 was answered by the construction and integration of four different concepts. These concepts were selected from insights from the literature review on sub-question 1 and 2, which were: (1) an open-system refugee camp, (2) a COVID-19 transmission model, (3) COVID-19 vaccine allocation strategies and (4) restricting COVID-19 measures on camp openness.

The first concept describes a system of interactions between refugees and a host community, applied to the Rohingya refugee camp context. These interactions were conceptualized through a daily activity schedule, guiding the visiting of either an in-camp facility or the vicinity market along the refugee camp boundaries. Here, an important simplification was the aggregation of all in-camp activities & interactions into one type of activity. Most importantly, the ratio of refugees and host communities was determined for each location, to represent the likeliness of interactions between the two populations. As both usually meet at the vicinity market, for this place a higher chance of meeting an individual from the Bangladesh host community was formalized. The second concept builds forth on an existing epidemic (SEIR) model, which are used to model the transmission process of an infectious virus. A SEIR model differentiates between different infection stages, namely for people who are susceptible, exposed, (a)symptomatically infected, recovered or dead. To study the influence of COVID-19 vaccines, the infection stage *vaccinated* was integrated. Infection stages were assumed not to change from susceptible to exposed in case of being vaccinated. The third concept *vaccine allocation strategies* was introduced in the answering of sub-question 2. Five vaccine allocation strategies were considered, which were conceptualized through the determination of which individuals receive a vaccine and when. The receiving of a vaccine was based on this allocation strategy, differentiating the Rohingya & host community populations over age groups. Based on the availability of vaccines, allocation took place for these priority groups. The fourth concept was introduced in the answering of sub-question 1. Camp openness was conceptualized by either fully closing, partially closing or fully opening the camp. Also, camp openness for in-camp facilities was considered a factor, which was conceptualized as the (partial) closing of the vicinity markets. Next to these physical measures for limiting people's movements in the camp, non-physical measures were considered based on *refugee compliance* to stay home in case of being sick, wearing masks and to keep non-vaccinated home as a household.

Through *process diagramming* and UML-based concepts and by reviewing existing data on the Rohingya camps, an integrated concept was defined. This integrated concept was used as a basis for grasping a conceptual model and serves as a basis for studying the dynamics between the different sub-concepts.

10.1.4 Sub-question 4

How can this formalized concept be integrated with an existing agent-based model on COVID-19 infections in refugee camp settlements?

Sub-question 4 was answered by implementing the integrated concept into an existing ABM model for the spread of COVID-19 in a refugee camp. The model was built in *Netlogo*, an ABM supportive programming language. The goal was to combine elements from the existing model, which was mainly stylistic, and to translate these and the new concepts from sub-question 3 into the context of the Rohingya refugee camps. To do so, three main adjustments were made in the existing model: (1) adding *camp openness*, (2) extend the epidemic model with COVID-19 vaccines and (3) translate elements to the case study context of the Rohingya refugee camps. The model was built with in an interactive model interface, which can be used to visualize model outcomes. Running the model is done in discrete time steps, and consists of model parameters which are derived from the defined sub-concepts. To make sure every mechanism in the model works as intended, different verification techniques were applied during the modeling. In this model, a small fraction of the Nayapara RC Rohingya refugee camp is reflected. The population of study is approximately 900 Rohingyas and 300 host community people, who interact on a daily basis. Running the model will reflect these interactions and following COVID-19 infections. To compare vaccine allocation strategies, one can select a vaccine allocation strategy and the number of vaccines available.

10.1.5 Sub-question 5

How can the dynamics between COVID-19 infections in an open-system refugee camp settlement and vaccine allocation strategies be explained with an agent-based experimental simulation study?

Sub-question 5 was answered by the setup and execution of various model experiments and by the identification, reporting and visualization of the results from these experiments. The dynamics between infections and interactions can be influenced by different types of limited camp openness and by the allocation of vaccines trough different strategies. To conclude on their (shared) effectiveness, several mention-worthy factors were found relating to both. Starting with the effect of limited camp openness on the dynamics between interactions and infections, model results show three important insights deciding effective control over infections. The first two insights relate to the role of host communities influencing the COVID-19 infections trajectory in an open-system camp. Firstly, a clear insight is the fact that host communities can undoubtedly be a potential source of an outbreak. Model results show if the camp is completely healthy, refugee-host interactions with infected host communities can be the trigger for a large outbreak in the camp covering over at least 90% of the refugee population. Secondly, model results do not show that influxes of host communities significantly determine the speed of the outbreak. In general, an introduction of infections will lead to a large outbreak which leads to a tipping point in 30 days and is large enough to cover the full refugee population. This relates to the third insight, which explains the main reason for the fast development of infections: an important cause of infections is found to be on locations with high concentrations of people. In the open-system camp, it was found at least infections are most likely to occur at the vicinity market (40%) and in-camp markets (38%). Due to high concentrations of both refugees and host communities, the risk of an outbreak is mainly concentrated here. Therefore, instead of keeping host communities out of the camp, a more effective way to control infections in the open-system camp is to implement dynamic camp openness based on the evaluation of weekly infections. The opening/closing of the camp for host communities and its markets for both refugees and host communities shows to be an effective measure for reducing infections, but still maintaining a degree of interactive freedom. An advantage here is that refugee-host interactions can still be tolerated by more than 60% compared to an unconditional lockdown, whereas the speed of spread and total number of infections remains equally controlled.

The implementation of vaccines also positively influences the dynamics between interactions and infections. Five factors were found to be important for weighing the effectiveness of different vaccine allocation strategies which define how vaccines are implemented. The two most important factors here are the (1) average *force of infection/susceptibility* and (2) average *risk of transmission*. Namely, these factors were found to be most influential for reducing total infections, as both the prioritization of elderly (EF strategy) or transmission groups (TG strategy) performed most effective on this criterion. Prioritizing elderly is effective, as a relatively large share of highly susceptible individuals are vaccinated in an early stage. Prioritizing transmission groups is effective as a large share of age-groups with a high risk transmission profile can be vaccinated. These factors also explain why the prioritization of children (CF strategy) and creating equal access of vaccines is less effective: although children are over-represented in the population (60%) and therefore cover a potential high risk of transmission, their contribution to total infections is relatively low. Equal access of vaccines (through the EQ strategy) is less effective as it results in an under-representation of either vaccinated transmission groups or elderly, explaining their lower effectiveness compared to the EF strategy and TG strategy.

When comparing different strategies, three other factors are concluded important: (3) the *rate of symptomatic infections*, (4) *vaccine availability* and (5) *vaccine infectiousness*. The third factor decides a strategy's effectiveness from a health-based perspective. For minimizing severe and critical infections, prioritizing high risk groups is most effective. In this research, vaccinating elderly and older adults first is most effective here, as these age-groups have the highest risk of a serious infection. Also, it explains the ineffectiveness of the BO strategy, for the simple reason insufficient refugees are vaccinated. Both factor 4 and 5 highlight the sensitivity/robustness of the strategies. Namely, a higher vaccine availability stabilizes the effectiveness of each strategy, which is most robust for the EF strategy and TG strategy. But when comparing these two strategies, an important difference between the two is reflected when vaccine infectiousness is assumed. Namely, prioritizing transmission groups results in a significant stronger increase of total infections compared to any other strategy. The main reason for this is the higher share of infectious, vaccinated age-groups with a high-risk transmission profile, which in that case reduces effectiveness of this strategy.

A last finding on the dynamics between infections and interactions is the fact that a combined implementation of both camp openness restrictions and vaccines further increase the effective control over infections. Here, a significant degree of freedom to interact by refugees and host communities can be maintained, especially when vaccinated people can visit markets unconditionally. Several model experiments point out that total infections can on average be further reduced by 32%. By allowing vaccinated people, refugee-host interactions can further increase by at least 10%. Here, the TG strategy creates most interactive freedom, as this strategy covers highest share of vaccinated age-groups who frequently visit markets. However, a pitfall of this strategy is reflected by its relative high share of severe/critical infections. And when vaccinated individuals are infectious, this difference is even further highlighted for this strategy. The alternative is to implement the EF strategy, which illustrates the main trade-off which follows from studying the dynamics between infections, interactions. Namely, vaccinating elderly first would result in significantly lower severe/critical infections (60%), but is less effective to allow for economic activities between refugees and host communities (which is 8% less for this strategy).

10.1.6 Sub-question 6

How can the outcomes of this study be translated to an effective strategy for COVID-19 vaccine allocation in a refugee camp?

Sub-question 6 was answered by validating and interpreting model outcomes and translate these to real-world advises in context of the COVID-19 Rohingya Response in Bangladesh. Here, the aim is to not only consider these model outcomes and their interpreted (un)desired effects, but to also put these into broader perspective. To translate the conclusions which were drawn in previous section to an effective strategy, four main factors were used to compare the effectiveness of each strategy: (1) keeping control over total infections, (2) reducing risks of severe/critical infections, (3) sensitivity for vaccine infectiousness and (4) maximize the tolerated number of refugee-host interactions.

In general, dynamic regulation of camp openness is judged an effective strategy to control infections, and it can sustain a 60% higher degree of economic freedom between refugees and host communities compared to completely locking down the camp. Therefore, this type of camp openness regulation is effective from both an economic and health-based perspective. However, two general implications should be considered as well, which are interpreted to influence the effectiveness of dynamic camp openness. Firstly, regulating camp openness does not necessarily mean that behavior of refugees inside the camp can be effectively managed. Other studies conclude the steering of the behavior of Rohingya refugees is complex, and fully limiting camp openness is physically a challenging task. Secondly, effective dynamic camp openness regulation is dependent on frequent and intensive testing of COVID-19 cases. If not done properly, the effectiveness of dynamic camp openness will likely be significantly lower.

The effectiveness of dynamic camp openness can be further improved in combination with the implementation of vaccines. The vaccine allocation strategies which are most in favour of these factors are the Elderly first and the Transmission group strategy, as these can most effectively reduce infections and can allow for a higher level of tolerated refugee-host interactions. Other strategies were found to be less effective on these factors. When deciding between the prioritization of elderly or transmission groups, a trade-off on health and economic values should be weighed. From an economic point of view, it is most effective to vaccinate highly transmitting young adults first. People in this age-group are most active, and are therefore an effective target for giving highest priority to revive the economic participation in economic activities. But from a health-based point of view, it is more effective to prioritize elderly. Although elderly contribute less to the economic activities, the health-related risks can most effectively be reduced as the risk of severe and critical infections is highest for this age-group. This trade-off is highlighted in particular if the prioritization of transmission groups is considered in combination with always allowing vaccinated people at markets. Namely, this strategy is found to be most sensitive to vaccine infectiousness, which risks to further increase severe/critical infections among non-vaccinated age-groups.

In general, it can be concluded that the selection of one of these strategies is an ethical problem of weighing the economic losses/benefits versus the implications following from health-related risks. This research does not propose a solution to this question, but rather marks and quantifies this trade-off.

10.2 ANSWERING THE MAIN RESEARCH QUESTION

Having answered each sub-question separately, an answer can be given to the main research question. The main research question in this study was formulated: *What vaccine allocation strategies can be identified as an effective trade-off between allowing individual interactions and controlling COVID-19 infections in an open-system refugee camp settlement?*

The goal in this research was to study the dynamics between different vaccine allocation strategies, COVID-19 infections and refugee-host interactions in the Rohingya camps in Bangladesh and to find an effective trade-off which balances two KPIs: COVID-19 infections and refugee-host interactions. Refugee-host interactions are considered an important source of livelihood-generation, from which both the Rohingya and the host community populations reap the benefits from and takes away some of their dependencies on external aid. COVID-19 infections are considered an important measure which represents COVID-19's threat to the Bangladesh health system, and are assumed to be a result of refugee-host interactions. As reducing COVID-19 infections and allowing more interactions between individuals are conflicting objectives, this research considers COVID-19 vaccines as a more long-term solution for obtaining these objectives both.

To do so, the dynamics between four sub-concepts were studied: (1) an open-system refugee camp, (2) a COVID-19 transmission model, (3) COVID-19 vaccine allocation strategies and (4) restricting COVID-19 measures on camp openness. These concepts were integrated and analysed with an ABM model, which lead to insights which can be used for improved decision-making on the COVID-19 response in the Rohingya Camps. For example, it can be used by the Government of Bangladesh and humanitarian aid organizations who coordinate the COVID-19 Vaccine Program in Bangladesh.

Here, it is important to mention that this research does not aim to propose a *single best* solution. This research does not use optimization techniques for finding the optimal trade-offs between COVID-19 infections and refugee-host interactions. Nor does this research claim to grasp and weigh all ethical values and contextual dependencies when comparing the effectiveness of vaccine allocation strategies and studying the dynamics between the aforementioned concepts. As the system of study consists of many different parameters and concepts are simplified, outcomes in this study cope with levels of uncertainty and are subjective for interpretation. However, insights from this research should be interpreted based on their exploratory character. Namely, several effects of single and combined model parameters were measured, which give a good indication on the behavior of the system of study, the relations and dependencies between sub-concepts and the influence of different restricting and benefiting policy measures.

The model outcomes an the interpretation of these outcomes have lead to the following conclusion on an effective strategy to allow refugee-host interactions and control COVID-19 infections in an open-system refugee camp. First of all, the open character of a refugee camp with interactions between refugees and host communities should be judged a significant source of triggering infections. However, it is not a solution to keep out host communities from the camp environment to prevent an outbreak. Namely, given the fact that complete isolation of the Rohingya camps is barely possible, an infection will likely be registered inside the camp. As the refugee camps are overcrowded, an outbreak will still be likely as shown in the model results. Here, the influence of the host communities of the scale of the outbreak is negligible. Rather, a combination of opening/closing the camp based on the evaluation of periodical infection-rates and a well-informed selection of a vaccine allocation strategy is concluded to be effective. This is beneficial from an economic and health-based perspective: it maximizes the level of tolerated interactions between refugees and host communities and maintains a sufficient control over the infection trajectory in the open camp environment. To maximize the effectiveness of this strategy, it is concluded that either elderly or transmission groups should be prioritized; both maximize the reduction of infections, which for other strategies were not found to be significantly less effective. The selection of a strategy which prioritizes elderly or transmission groups is an ethical trade-off between economic and health-based losses/benefits. For maximizing tolerated numbers of economic interactions between refugees and host communities, it is most effective to prioritize transmission groups. For minimizing health-related risks for vulnerable age-groups, the prioritization of elderly is more effective. This trade-off is illustrated in figure 10.1.

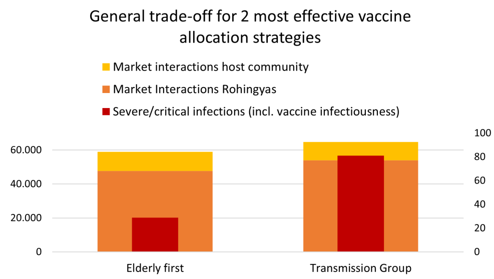


Figure 10.1: The main trade-off for an effective strategy for refugee-host interactions & severe/-critical infections

For translating these conclusions to an effective strategy which apply to the real-world context of the Rohingya refugees, context-dependent factors and limitations of the model should be considered as well. Based on model validations, model outcomes are judged valid for supporting well-informed decision-making. Namely, model validation by comparing the results in this study with other studies indicated a strong theoretical validity. Especially for the effects of different levels of camp openness strictness and the measuring of stay-at-home, results were similar to other studies. Also, this research produces similar results for different vaccine allocation strategies. As this theoretical comparison indicates a high validity of the model results, the outcomes are judged to be a strong theoretical basis to support decision-making. Based on this judgement, many of the model results can be used as a good indication for what would happen when implementing different policies in line with the results as discussed for answering sub-question 5.

However, the chaotic nature of a refugee camp is concluded barrier for the feasibility of implementing a strategy. Imposing limitations on the freedom of Rohingyas to interact is hard, as it demands a structural change in their behavior. Also, the physical characteristics of the open-system refugee camp do not lend themselves well for implementing measures and for monitoring the effectiveness of the strategy. Also, from expert consultation it could be concluded the model misses some contextual factors, which could not all be captured in the model. For example, a factor which was not included in the model was willingness to get vaccinated. From insights from expert interviews however, this is an important factor. Apart from contextual implications, limitations exist on the simplifications and assumptions and the resolution of the model. Simplifications were made to grasp different sub-concepts in one model and to make it computationally less intensive, which reduces the high context-specific nature of the system of study. Most influencing limitations regarding this were judged as follows: (1) the low resolution of different types of interactions between Rohingyas between themselves, potentially underestimating the estimation of infections among Rohingyas; (2) The simplified concept of risking a COVID-19 infection, which was only based on spending time with & distance to infected others, whereas more factors play a role in transmissions; (3) The relative low resolution of differentiating age-groups for vaccine allocation strategies, which indicates lower differences between the strategies; And (4) the overestimation of *known* *infections* inside the camp environment which was assumed to set camp openness. In reality, known cases are lower. A last more general limitation relates to model resolution of time and space. Time is modeled for 90 days, but with high resolution (time steps of only 5 minutes), which makes the model computationally intensive. Therefore, robustness of the model parameters was not fully discovered. Modeling space was done with high resolution as well, with a potential underestimation of COVID-19 infections as a result as only a fraction of the camp was modeled in isolation, leaving out interactions with other Rohingyas.

10.3 RECOMMENDATIONS TO IMPROVE THE COVID-19 RESPONSE FOR ROHINGYAS IN BANGLADESH

The conclusions drawn in previous sections can be used by decision-makers on the COVID-19 response for Rohingyas in Bangladesh. For example, insights can be used by the Government of Bangladesh, who is the main coordinator of the Rohingya Refugee response. Also, insights can be used by humanitarian aid organizations who cooperatively work with the Government of Bangladesh.

Since the outbreak of COVID-19, the Government's Ministry of Health, together with UNHCR and WHO, raised a Technical Advisory Committee on Immunization of Rohingyas. This committee was raised to review and assess the potential challenges faced in the roll-out of the vaccine program among the Rohingyas. Also, a Strategic Advisory Group was raised, which was initiated to coordinate the practical implementation of this program and in line with the NDVP. At the time of writing, vaccine programs are starting up and the above described committees are set to meet each week. Here, it is assessed what new insights are gained which can be used for adaption in the vaccine programs. Results and insights from this research can be used as an academic, guiding basis for more informed decision-making on the prioritization strategies for COVID-19 vaccines.

Based on the outcomes of this research, success for effective introduction and implementation of COVID-19 vaccines can be raised when considering a vaccine allocation strategy which focuses on the prioritization of individuals which contribute most to the transmission of COVID-19. A strategy as such has shown to be most effective for reducing COVID-19 infections inside the Rohingya camp environment, and can therefore most effectively ensure a more rapid reopening of the camp environment.

It is not recommended to distribute vaccines equally among individuals, or to exclude Rohingyas from the vaccination program. Both these strategies show no effective reduction of infections, which is undesirable. Creating equal access of vaccines for everyone can considered ethically fair, but does not reduce effective numbers of infections. Exclusion of Rohingyas is judged an undesirable strategy for a practical and an ethical reason: firstly, it does not effectively reduce COVID-19 infections, which raises the risk of spill-overs of infections from the camp to outside. A second reason is that it is ethically irresponsible to exclude a population, based on their cultural background [HRW, 2021].

Lastly, a combination of vaccine and non-vaccine related measures is advised. Vaccines have a significant influence on effectively reducing COVID-19 infections, but this effect is enforced in combination with other, contact reducing measures. To increase the speed of potentially reopening the Rohingya camp environment and bring life back to normal, a maintaining of contact reducing measures is advised, especially for the initial times of vaccine delivery. Namely, the first 30 days are most crucial for reducing COVID-19 infections, as the speed of spread in a refugee camp is high.

A final recommendation is not to judge the outcomes from this research in isolation. It is advised to also consider contextual factors when weighing insights from this study for real-world implementation. Several studies point towards these context-dependencies, and it is crucial to incorporate these. For example, a vaccine allocation strategy does not stand alone for an effective response. For example, effective allocation of vaccines is also dependent on a high willingness to get vaccinated by the population, which highlights the importance of communication with the Rohingyas. Therefore, decision-making on the picking of an allocation strategy can be improved if people are aware and eager to get vaccinated.

10.4 SCIENTIFIC CONTRIBUTION OF THIS RESEARCH

Next to the societal relevance of this study, this research also represents scientific value. As mention in the research gap, no studies can be found which study different COVID-19 vaccine allocation strategies in context of refugee camps. Therefore, this research adds value to two branches of literature, relating to literature on *logistics in the vaccine supply chain* and literature on effective *COVID-19 responses in refugee camps*.

The vaccine supply chain has been studied extensively, as stated and reviewed by Duijzer et al. [2018]. Vaccine allocation is one of its core elements, and should be judged a very important element in decision-making, especially when vaccines are scarce [Duijzer et al., 2018]. On top of that, vaccine allocation is judged the only 'unique' element of the vaccine supply chain when comparing with other supply chains [Duijzer et al., 2018; Dasaklis et al., 2012]. Therefore, the need for up-to-date and context specific insights on this vaccine allocation process is an important insight for supported decision-making.

Secondly, this research adds value to scientific research on COVID-19 responses in refugee camps, related to the dynamics between the four concepts which were introduced. As will be introduced in chapter 2, various literature studies exist which highlight one or two of these concepts. However, up to the writers knowledge, no literature exists on the balancing effect of vaccine allocation strategies, COVID-19 transmissions, and movement-restricting measures in an open-system refugee camp environment. By studying the dynamics between these concepts, a new light is shed on the branch of literature which supports decision-making in refugee camp environments in combinations with infectious diseases and epidemics.

10.5 RECOMMENDATIONS FOR FURTHER RESEARCH

This research holds some interesting recommendations for further research. Namely, some of the researched concepts still leave room for more practical or in-depth academic insights. Recommendations are categorised in two branches: (1) focusing on a more in-depth analysis of concepts and (2) focusing on a more in-depth analysis of the robustness of the model outcomes from this study.

For the first category, future research is needed which more explicitly analyses the dynamics between infections and interactions. In this research, infections were only modeled as a result of chance of meeting someone infected and getting infected from that. However, the dynamics between interactions and infections are far more complex. For example, gender-specific transmission processes differ [Metelmann et al., 2021], indoor and outdoor transmission processes or most likely different [Habeebullah et al., 2021], face-to-face contacts increase the chance of transmission [Chen et al., 2021] and symptomatic infections are also contribute more to infecting others [Vermund and Pitzer, 2021]. These factors are important for this research, as some markets in the open-system are covered/indoor, and men are most frequent visitors of local markets. Also, this study does not make use of social mixing matrices, which is frequently used for studying epidemic spreads. For example, Foy et al. [2021] implements social-mixing matrices for different ages, as age-groups are more likely to interact with themselves. In this way, future research would for example allow to study if it is possible to let children always go to school, as they cluster here only with their peers. A second recommendation is to study a more flexible application of different vaccine allocation strategies. Tuite et al. [2010] found for the Influenza outbreak, a flexible policy to switch between different strategies over time can be an effective strategy. In this research, a relatively static strategy was applied, as the allocation of vaccines was only differentiated over available batches. In future research, a dynamic applications of different strategies can be studied as well. Furthermore, regarding the effectiveness of vaccine allocation strategies, future research could differentiate further over different age-groups. As age-groups were used to define prioritization groups, a more broad differentiation between age-groups can be applied. Namely, Foy et al. [2021] and Shim [2021] both study ten age-groups, whereas this research only considers four. Differentiating over more different age-groups allows for more explicit modeling the transmission process (which differs over different ages). One can further explicate transmission forces, symptomatic rates or different interaction patterns over age. In this way, differences between strategies can come forward more explicitly and raises a study's relevancy for real-world application [Davies et al., 2020].

Regarding the second category is to further research the robustness of the model outcomes from the model which is used for analysis. A main limitation of this study is the fact that not the full scenario space over the range of model parameters has been discovered. Namely, due to a lack of time and highly computational model, experiments could not be run over a complete range of model parameter ranges. With more insights on the solution spaces of this model, more robust conclusions can be drawn which would further improve decision-making on an effective COVID-19 response in Rohingya camps. For doing so, it is suggested to analyse the ABM model from this research with the *EMA Workbench*. Exploratory Modeling and Analysis (EMA) is a research methodology which allows for further analyzing complex systems with large scenario spaces [Bankes, 1993]. By applying the EMA, model results can be analysed and used for decision making under deep uncertainty and robust decision-making.

BIBLIOGRAPHY

Aaby, K., Herrmann, J. W., Jordan, C. S., Treadwell, M., and Wood, K. (2006). Montgomery county's public health service uses operations research to plan emergency mass dispensing and vaccination clinics. *Interfaces*, 36(6):569–579.

ACAPS (2020). Acaps covid-19: Rohingya response risk report. *Rohingya Response Risk Report*.

Agblorti, S. K. M. and Awusabo-Asare, K. (2011). Refugee-host interaction in the krisan refugee settlement in ghana. *Ghana Journal of Geography*, 3:35–59.

Agblorti, S. M. (2006). Refugee-host interaction: Case of krisan refugee settlement in ghana.

Ahmed, N., Firoze, A., and Rahman, R. M. (2020). Machine learning for predicting landslide risk of rohingya refugee camp infrastructure. *Journal of Information and Telecommunication*, 4(2):175–198.

Ajelli, M., Gonçalves, B., Balcan, D., Colizza, V., Hu, H., Ramasco, J. J., Merler, S., and Vespignani, A. (2010). Comparing large-scale computational approaches to epidemic modeling: agent-based versus structured metapopulation models. *BMC infectious diseases*, 10(1):190.

Alam, N., Kenny, B., Maguire, J., McEwen, S., Sheel, M., and Tolosa, M. (2019). Field epidemiology in action: an australian perspective of epidemic response to the rohingya health emergencies in cox's bazar, bangladesh. *Global Biosecurity*, 1(1).

Alemi, Q., Stempel, C., Siddiq, H., and Kim, E. (2020). Refugees and covid-19: achieving a comprehensive public health response. *Bulletin of the World Health Organization*, 98(8):510.

Alix-Garcia, J., Walker, S., Bartlett, A., Onder, H., and Sanghi, A. (2018). Do refugee camps help or hurt hosts? the case of kakuma, kenya. *Journal of Development Economics*, 130:66–83.

Alloush, M., Taylor, J. E., Gupta, A., Valdes, R. I. R., and Gonzalez-Estrada, E. (2017). Economic life in refugee camps. *World Development*, 95:334–347.

Anderson, R. M., Heesterbeek, H., Klinkenberg, D., and Hollingsworth, T. D. (2020). How will country-based mitigation measures influence the course of the covid-19 epidemic? *The lancet*, 395(10228):931–934.

Anwar, S., Nasrullah, M., and Hosen, M. J. (2020). Covid-19 and bangladesh: Challenges and how to address them. *Frontiers in public health*, 8.

Araz, O. M., Galvani, A., and Meyers, L. A. (2012). Geographic prioritization of distributing pandemic influenza vaccines. *Health Care Management Science*, 15(3):175–187.

Azad, A. and Jasmin, F. (2013). Durable solutions to the protracted refugee situation: The case of rohingyas in bangladesh. *Journal of Indian Research*, 1(4):25–35.

Bakewell, O. (2002). Document. refugee aid and protection in rural africa: working in parallel or cross-purposes? *Refugee Survey Quarterly*, 21(1_and_2):228–241.

Bala, B. K., Arshad, F. M., and Noh, K. M. (2017). Causal loop diagrams. In *System dynamics*, pages 37–51. Springer.

Ball, F., Britton, T., and Lyne, O. (2004). Stochastic multitype epidemics in a community of households: estimation and form of optimal vaccination schemes. *Mathematical biosciences*, 191(1):19–40.

Ball, F. and Lyne, O. (2006). Optimal vaccination schemes for epidemics among a population of households, with application to variola minor in brazil. *Statistical Methods in Medical Research*, 15(5):481–497.

Ball, F. G. and Lyne, O. D. (2002). Optimal vaccination policies for stochastic epidemics among a population of households. *Mathematical Biosciences*, 177:333–354.

Banik, R., Rahman, M., Hossain, M. M., Sikder, M. T., and Gozal, D. (2020). Covid-19 pandemic and rohingya refugees in bangladesh: What are the major concerns? *Global Public Health*, 15(10):1578–1581.

Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations research*, 41(3):435–449.

Barbera, J., Macintyre, A., Gostin, L., Inglesby, T., O'toole, T., DeAtley, C., Tonat, K., and Layton, M. (2001). Large-scale quarantine following biological terrorism in the united states: scientific examination, logistic and legal limits, and possible consequences. *Jama*, 286(21):2711–2717.

Barrios, J. M., Benmelech, E., Hochberg, Y. V., Sapienza, P., and Zingales, L. (2021). Civic capital and social distancing during the covid-19 pandemic. *Journal of public economics*, 193:104310.

Bartovic, J., Datta, S. S., Severoni, S., and D'Anna, V. (2021). Ensuring equitable access to vaccines for refugees and migrants during the covid-19 pandemic. *World Health Organization. Bulletin of the World Health Organization*, 99(1):3–3A.

Becker, N. G. and Starczak, D. N. (1997). Optimal vaccination strategies for a community of households. *Mathematical Biosciences*, 139(2):117–132.

Beech, H. and Hubbard, B. (2020). Unprepared for the worst: world's most vulnerable brace for virus.

Betts, A., Bloom, L., Kaplan, J. D., and Omata, N. (2014). *Refugee economies: Rethinking popular assumptions*. University of Oxford, Refugee Studies Centre.

Betts, A., Delius, A., Rodgers, C., Sterck, O., and Stierna, M. (2019). Doing business in kakuma: refugees, entrepreneurship, and the food market.

Bhatia, A., Mahmud, A., Fuller, A., Shin, R., Rahman, A., Shatil, T., Sultana, M., Morshed, K. M., Leaning, J., and Balsari, S. (2018). The rohingya in cox's bazar: when the stateless seek refuge. *Health and human rights*, 20(2):105.

Bi, Q., Wu, Y., Mei, S., Ye, C., Zou, X., Zhang, Z., Liu, X., Wei, L., Truelove, S. A., Zhang, T., et al. (2020). Epidemiology and transmission of covid-19 in shenzhen china: Analysis of 391 cases and 1,286 of their close contacts. *MedRxiv*.

Biswas, M. H. A., Paiva, L. T., and De Pinho, M. (2014). A seir model for control of infectious diseases with constraints. *Mathematical Biosciences & Engineering*, 11(4):761.

Bodrud-Doza, M., Shammi, M., Bahlman, L., Islam, A. R. M., Rahman, M., et al. (2020). Psychosocial and socio-economic crisis in bangladesh due to covid-19 pandemic: a perception-based assessment. *Frontiers in public health*, 8:341.

Brodeur, A., Grigoryeva, I., and Kattan, L. (2020). Stay-at-home orders, social distancing and trust.

Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., and Rubin, G. J. (2020). The psychological impact of quarantine and how to reduce it: rapid review of the evidence. *The lancet*, 395(10227):912–920.

Bubar, K. M., Reinholt, K., Kissler, S. M., Lipsitch, M., Cobey, S., Grad, Y. H., and Larremore, D. B. (2021). Model-informed covid-19 vaccine prioritization strategies by age and serostatus. *Science*, 371(6532):916–921.

Buckner, J. H., Chowell, G., and Springborn, M. R. (2020). Optimal dynamic prioritization of scarce covid-19 vaccines. *medRxiv*.

Buheji, M., Mavrić, B., Beka, G., Yein, T. C., et al. (2020). Alleviation of refugees covid-19 pandemic risks-a framework for uncertainty mitigation. *International Business Research*, 13(7):69–79.

Bukuluki, P., Mwenyango, H., Katongole, S. P., Sidhva, D., and Palattiyil, G. (2020). The socio-economic and psychosocial impact of covid-19 pandemic on urban refugees in uganda. *Social Sciences & Humanities Open*, 2(1):100045.

Bullock, J., Cuesta-Lazaro, C., Quera-Bofarull, A., Katta, A., Pham, K. H., Hoover, B., Strobelt, H., Jimenez, R. M., Sedgewick, A., Evers, E. S., et al. (2021). Operational response simulation tool for epidemics within refugee and idp settlements. *medRxiv*.

Cavaglieri, S. (2008). Livelihoods & micro-finance in refugee camps. *Maste', s thesis, University of Roma Italy*.

Chan, H. F., Brumpton, M., Macintyre, A., Arapoc, J., Savage, D. A., Skali, A., Stadelmann, D., and Torgler, B. (2020). How confidence in health care systems affects mobility and compliance during the covid-19 pandemic. *PloS one*, 15(10):e0240644.

Chapman, L. A., Shukla, P., Rodríguez-Barraquer, I., Shete, P. B., León, T. M., Bibbins-Domingo, K., Rutherford, G. W., Schechter, R., and Lo, N. C. (2021). Comparison of covid-19 vaccine prioritization strategies in the united states. *medRxiv*.

Chen, B., Jia, P., and Han, J. (2021). Role of indoor aerosols for covid-19 viral transmission: a review. *Environmental Chemistry Letters*, pages 1–18.

Chopra, S. and Meindl, P. (2007). Supply chain management. strategy, planning & operation. In *Das summa summarum des management*, pages 265–275. Springer.

Chu, D. K., Akl, E. A., Duda, S., Solo, K., Yaacoub, S., Schünemann, H. J., El-harakeh, A., Bognanni, A., Lotfi, T., Loeb, M., et al. (2020). Physical distancing, face masks, and eye protection to prevent person-to-person transmission of sars-cov-2 and covid-19: a systematic review and meta-analysis. *The Lancet*, 395(10242):1973–1987.

Crooks, A. T. and Hailegiorgis, A. B. (2014). An agent-based modeling approach applied to the spread of cholera. *Environmental Modelling & Software*, 62:164–177.

Dalgıç, Ö. O., Özaltın, O. Y., Ciccotelli, W. A., and Erenay, F. S. (2017). Deriving effective vaccine allocation strategies for pandemic influenza: Comparison of an agent-based simulation and a compartmental model. *PloS one*, 12(2):e0172261.

Dasaklis, T. K., Pappis, C. P., and Rachaniotis, N. P. (2012). Epidemics control and logistics operations: A review. *International Journal of Production Economics*, 139(2):393–410.

Davies, N. G., Abbott, S., Barnard, R. C., Jarvis, C. I., Kucharski, A. J., Munday, J., Pearson, C. A., Russell, T. W., Tully, D. C., Washburne, A. D., et al. (2021). Estimated transmissibility and severity of novel sars-cov-2 variant of concern 202012/01 in england. *MedRxiv*, pages 2020–12.

Davies, N. G., Klepac, P., Liu, Y., Prem, K., Jit, M., and Eggo, R. M. (2020). Age-dependent effects in the transmission and control of covid-19 epidemics. *Nature medicine*, 26(8):1205–1211.

Dempster, H., Ginn, T., Graham, J., Ble, M. G., Jayasinghe, D., and Shorey, B. (2020). Locked down and left behind: the impact of covid-19 on refugees' economic inclusion. *Center for Global Development, Refugees International, and International Rescue Committee.* https://www.refugeesinternational.org/reports/2020/7/6/locked-down-and-left-behind-the-impact-of-covid-19-on-refugees-economic-inclusion. *Published July*, 8.

Dobing, B. and Parsons, J. (2008). Dimensions of uml diagram use: a survey of practitioners. *Journal of Database Management (JDM)*, 19(1):1–18.

Duan, H., Wang, S., and Yang, C. (2020). "coronavirus: limit short-term economic damage". *Nature*, 578(7796):515.

Duijzer, L. E., van Jaarsveld, W., and Dekker, R. (2018). Literature review: The vaccine supply chain. *European Journal of Operational Research*, 268(1):174–192.

Dushoff, J., Plotkin, J. B., Viboud, C., Simonsen, L., Miller, M., Loeb, M., and David, J. (2007). Vaccinating to protect a vulnerable subpopulation. *PLoS Med*, 4(5):e174.

Easton-Calabria, E. E. (2015). From bottom-up to top-down: The 'pre-history'of refugee livelihoods assistance from 1919 to 1979. *Journal of Refugee Studies*, 28(3):412–436.

El-Khatib, Z., Al Nsour, M., Khader, Y. S., and Abu Khudair, M. (2020). Mental health support in jordan for the general population and for the refugees in the zaatari camp during the period of covid-19 lockdown. *Psychological Trauma: Theory, Research, Practice, and Policy*, 12(5):511.

Farrell, T. W., Francis, L., and Lundebjerg, N. E. (2020). The later innings of life: Implications of covid-19 resource allocation strategies for older adults. *Journal of the American Geriatrics Society*.

Farzana, K. F. (2016). Voices of the burmese rohingya refugees: Everyday politics of survival in refugee camps in bangladesh. *Journal of Social Science and Humanities*, 24(1):131–150.

Fauci, A. S., Lane, H. C., and Redfield, R. R. (2020). Covid-19—navigating the uncharted.

Filipski, M. J., Rosenbach, G., Tiburcio, E., Dorosh, P., and Hoddinott, J. (2020). Refugees who mean business: Economic activities in and around the rohingya settlements in bangladesh. *Journal of Refugee Studies*.

Fowler, J. H., Hill, S. J., Levin, R., and Obradovich, N. (2020). The effect of stay-at-home orders on covid-19 infections in the united states. *arXiv preprint arXiv:2004.06098*.

Foy, B. H., Wahl, B., Mehta, K., Shet, A., Menon, G. I., and Britto, C. (2021). Comparing covid-19 vaccine allocation strategies in india: A mathematical modelling study. *International Journal of Infectious Diseases*, 103:431–438.

Garcia-Beltran, W. F., Lam, E. C., Denis, K. S., Nitido, A. D., Garcia, Z. H., Hauser, B. M., Feldman, J., Pavlovic, M. N., Gregory, D. J., Poznansky, M. C., et al. (2021). Multiple sars-cov-2 variants escape neutralization by vaccine-induced humoral immunity. *Cell*.

Gaynor, T. (2021). Q&a: 'including refugees in the vaccine rollout is key to ending the pandemic'. Retrieved on February 1st, 2021 on: https://www.unhcr.org/news/latest/2021/1/5fff1afe4/qa-including-refugees-vaccine-rollout-key-ending-pandemic.html publisher = UNHCR.

Gilman, R. T., Mahroof-Shaffi, S., Harkensee, C., and Chamberlain, A. T. (2020). Modelling interventions to control covid-19 outbreaks in a refugee camp. *BMJ global health*, 5(12):e003727.

Global COVID-19 Consortium (2021). Together we can. the covid-19 impact on stateless people & a roadmap for change. Technical report.

Godin, M. (2020). Covid-19 outbreaks are now emerging in refugee camps. why did it take so long for the virus to reach them? *Time Magazine*.

Goldstein, E., Wallinga, J., and Lipsitch, M. (2012). Vaccine allocation in a declining epidemic. *Journal of The Royal Society Interface*, 9(76):2798–2803.

Goolsbee, A. and Syverson, C. (2021). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of public economics*, 193:104311.

Government of Bangladesh et al. (2021). Operational guidelines for covid-19 vaccination for forcibly displaced myanmar nationals. Technical report, HPNSP.

Grauer, J., Löwen, H., and Liebchen, B. (2020). Strategic spatiotemporal vaccine distribution increases the survival rate in an infectious disease like covid-19. *Scientific reports*, 10(1):1–10.

Gruber, T. R. (1993). A translation approach to portable ontology specifications. *Knowledge acquisition*, 5(2):199–220.

Gupta, R. and Morain, S. R. (2021). Ethical allocation of future covid-19 vaccines. *Journal of medical ethics*, 47(3):137–141.

Habeebullah, T. M., Abd El-Rahim, I. H., and Morsy, E. A. (2021). Impact of outdoor and indoor meteorological conditions on the covid-19 transmission in the western region of saudi arabia. *Journal of environmental management*, 288:112392.

Hailegiorgis, A. and Crooks, A. T. (2012). Agent-based modeling for humanitarian issues: disease and refugee camps. In *The Computational Social Science Society of America Conference, Santa Fe, NM*.

HDX Data (2018). Cox's bazar refugee settlement infrastructure. data retrieved from HDX, https://data.humdata.org/dataset/cox-s-bazar-refugee-settlement-infrastructure.

HDX Data (2021). Rohingya refugees population by location at camp and union level - cox's bazar. data retrieved from HDX, https://data.humdata.org/dataset/site-location-of-rohingya-refugees-in-cox-s-bazar.

He, S., Peng, Y., and Sun, K. (2020). Seir modeling of the covid-19 and its dynamics. *Nonlinear Dynamics*, 101(3):1667–1680.

Helbing, D., Szolnoki, A., Perc, M., and Szabó, G. (2010). Evolutionary establishment of moral and double moral standards through spatial interactions. *PLoS Comput Biol*, 6(4):e1000758.

Hernandez-Suarez, C. M., Verme, P., Radyakin, S., and Murillo-Zamora, E. (2020). Covid-19 outbreaks in refugee camps. a simulation study. *medRxiv*.

Hogan, A., Winskill, P., Watson, O., Walker, P., Whittaker, C., Baguelin, M., Haw, D., Lochen, A., Gaythorpe, K., Ainslie, K., et al. (2020). Report 33: Modelling the allocation and impact of a covid-19 vaccine.

HRW (2021). Covid-19: A human rights checklist. Retrieved on February 1st, 2021 on: https://www.hrw.org/news/2020/04/14/covid-19-human-rights-checklist publisher = Human Rights Watch.

Hsan, K., Griffiths, M. D., Gozal, D., and Rahman, M. A. (2019). Hiv infection in rohingya refugees in bangladesh. *The Lancet HIV*, 6(7):e419.

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., Druckenmiller, H., Huang, L. Y., Hultgren, A., Krasovich, E., et al. (2020). The effect of large-scale anti-contagion policies on the covid-19 pandemic. *Nature*, 584(7820):262–267.

Hub, W. C. B. D. (6 April, 2021). Covid-19 dashboard. Retrieved on April 6th, 2021 on: https://cxb-epi.netlify.app/post/covid-19-dashboard/.

Humanitarian Response (2017). Cox's bazar : Reach- general infrastructure map - zone wise. data retrieved from Humanitarian Response & OCHA Services, https://www.humanitarianresponse.info/en/operations/bangladesh/infographic/coxs-bazar-reach-general-infrastructure-map-zone-wise.

IDC (2020). Situation report: Rohingya refugee crisis. Retrieved on February 12th, 2021 on: https://reliefweb.int/report/bangladesh/house-commons-international-development-committee-bangladesh-burma-androhingya.

Interview 1 (2021). Interview on rohingya refugee camps in bangladesh, covid-19 and vaccine allocation. Interview on March 29th, 2021.

Interview 2 (2021). Interview on rohingya refugee camps in bangladesh, covid-19 and vaccine allocation. Interview on March 31st, 2021.

Islam, M. M. and Yunus, M. Y. (2020). Rohingya refugees at high risk of covid-19 in bangladesh. *The Lancet Global Health*, 8(8):e993–e994.

Islam, M. S., Ira, J. I., Kabir, K. A., and Kamrujjaman, M. (2020). Effect of lockdown and isolation to suppress the covid-19 in bangladesh: an epidemic compartments model.

Jacobsen, K. (2002). Can refugees benefit the state? refugee resources and african statebuilding. *Journal of Modern African Studies*, pages 577–596.

Jalloh, M. F., Bennett, S. D., Alam, D., Kouta, P., Lourenço, D., Alamgir, M., Feldstein, L. R., Ehlman, D. C., Abad, N., Kapil, N., et al. (2019). Rapid behavioral assessment of barriers and opportunities to improve vaccination coverage among displaced rohingyas in bangladesh, january 2018. *Vaccine*, 37(6):833–838.

Jalloh, M. F., Wilhelm, E., Abad, N., and Prybylski, D. (2020). Mobilize to vaccinate: lessons learned from social mobilization for immunization in low and middle-income countries. *Human vaccines & immunotherapeutics*, 16(5):1208–1214.

Jeffries, R., Abdi, H., Ali, M., Bhuiyan, A. T. M. R. H., El Shazly, M., Harlass, S., Ishtiak, A., Mazhar, M. K. A., Prajapati, M., Pang, Q. Y., et al. (2021). The health response to the rohingya refugee crisis post august 2017: Reflections from two years of health sector coordination in cox's bazar, bangladesh. *PloS one*, 16(6):e0253013.

Jennings, N. R. (2000). On agent-based software engineering. *Artificial intelligence*, 117(2):277–296.

Jeong, H., Yim, H. W., Song, Y.-J., Ki, M., Min, J.-A., Cho, J., and Chae, J.-H. (2016). Mental health status of people isolated due to middle east respiratory syndrome. *Epidemiology and health*, 38.

Jerin, M. I., Mozumder, M. K., et al. (2019). Exploring host community attitudes towards rohingya refugees in bangladesh. *Intervention*, 17(2):169.

John Hopkins University (2021). Covid-19 dashboard by the center for systems science and engineering (csse) at johns hopkins university (jhu). Retrieved on January 7th, 2021 on: https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6.

Jørgensen, F., Bor, A., and Petersen, M. B. (2021). Compliance without fear: Individual-level protective behaviour during the first wave of the covid-19 pandemic. *British Journal of Health Psychology*, 26(2):679–696.

Kamal, A.-H., Huda, M., Dell, C., Hossain, S., and Ahmed, S. (2020). Translational strategies to control and prevent spread of covid-19 in the rohiynga refugee camps in bangladesh. *Global Biosecurity*, 1(4).

Keeling, M. J. and Ross, J. V. (2015). Optimal prophylactic vaccination in segregated populations: When can we improve on the equalising strategy? *Epidemics*, 11:7–13.

Keeling, M. J. and Shattock, A. (2012). Optimal but unequitable prophylactic distribution of vaccine. *Epidemics*, 4(2):78–85.

Kluge, H. H. P., Jakab, Z., Bartovic, J., d'Anna, V., and Severoni, S. (2020). Refugee and migrant health in the covid-19 response. *The Lancet*, 395(10232):1237–1239.

Kochhar, S., Rath, B., Seeber, L. D., Rundblad, G., Khamesipour, A., Ali, M., and Initiative, V. V. S. (2013). Introducing new vaccines in developing countries. *Expert review of vaccines*, 12(12):1465–1478.

Lam, E., McCarthy, A., and Brennan, M. (2015). Vaccine-preventable diseases in humanitarian emergencies among refugee and internally-displaced populations. *Hum Vaccin Immunother*, 11:2627–36.

Lauer, S. A., Grantz, K. H., Bi, Q., Jones, F. K., Zheng, Q., Meredith, H. R., Azman, A. S., Reich, N. G., and Lessler, J. (2020). The incubation period of coronavirus disease 2019 (covid-19) from publicly reported confirmed cases: estimation and application. *Annals of internal medicine*, 172(9):577–582.

Leamer, E. E. (1983). Let's take the con out of econometrics. *The American Economic Review*, 73(1):31–43.

Lewnard, J. A. and Lo, N. C. (2020). Scientific and ethical basis for social-distancing interventions against covid-19. *The Lancet Infectious Diseases*, 20(6):631–633.

Li, M. Y. and Muldowney, J. S. (1995). Global stability for the seir model in epidemiology. *Mathematical biosciences*, 125(2):155–164.

Ligmann-Zielinska, A., Kramer, D. B., Cheruvelil, K. S., and Soranno, P. A. (2014). Using uncertainty and sensitivity analyses in socioecological agent-based models to improve their analytical performance and policy relevance. *PloS one*, 9(10):e109779.

Linka, K., Peirlinck, M., and Kuhl, E. (2020). The reproduction number of covid-19 and its correlation with public health interventions. *Computational Mechanics*, 66(4):1035–1050.

Liu, Y., Gayle, A. A., Wilder-Smith, A., and Rocklöv, J. (2020). The reproductive number of covid-19 is higher compared to sars coronavirus. *Journal of travel medicine*.

Lopez-Pena, P., Davis, C. A., Mobarak, A. M., and Raihan, S. (2020). Prevalence of covid-19 symptoms, risk factors, and health behaviors in host and refugee communities in cox's bazar: A representative panel study. *Bull World Health Organ*.

Mahase, E. (2020). Covid-19: What is the r number?

Mamani, H., Chick, S. E., and Simchi-Levi, D. (2013). A game-theoretic model of international influenza vaccination coordination. *Management Science*, 59(7):1650–1670.

Mannan, A., Mehedi, H. H., Chy, N. U. H. A., Qayum, M. O., Akter, F., Rob, M., Biswas, P., Hossain, S., and Ayub, M. I. (2021). A multi-centre, cross-sectional study on coronavirus disease 2019 in bangladesh: clinical epidemiology and short-term outcomes in recovered individuals. *New Microbes and New Infections*, 40:100838.

Matrajt, L., Eaton, J., Leung, T., and Brown, E. R. (2020). Vaccine optimization for covid-19: who to vaccinate first? *medRxiv*.

Matrajt, L., Halloran, M. E., and Longini Jr, I. M. (2013). Optimal vaccine allocation for the early mitigation of pandemic influenza. *PLoS Comput Biol*, 9(3):e1002964.

Matrajt, L. and Longini Jr, I. M. (2010). Optimizing vaccine allocation at different points in time during an epidemic. *PloS one*, 5(11):e13767.

McGowan, C. R., Hellman, N., Chowdhury, S., Mannan, A., Newell, K., and Cummings, R. (2020). Covid-19 testing acceptability and uptake amongst the rohingya and host community in camp 21, teknaf, bangladesh. *Conflict and health*, 14(1):1–5.

Metelmann, S., Pattni, K., Brierley, L., Cavalerie, L., Caminade, C., Blagrove, M. S., Turner, J., Sharkey, K. J., and Baylis, M. (2021). Impact of climatic, demographic and disease control factors on the transmission dynamics of covid-19 in large cities worldwide. *One Health*, 12:100221.

Mohajan, H. (2018). History of rakhine state and the origin of the rohingya muslims.

Montclos, M.-A. P. d. and Kagwanja, P. M. (2000). Refugee camps or cities? the socio-economic dynamics of the dadaab and kakuma camps in northern kenya. *Journal of refugee studies*, 13(2):205–222.

Moyer, J. D. and Hedden, S. (2020). Are we on the right path to achieve the sustainable development goals? *World Development*, 127:104749.

Mukumbang, F. C. (2020). Are asylum seekers, refugees and foreign migrants considered in the covid-19 vaccine discourse? *BMJ global health*, 5(11):e004085.

Mylius, S. D., Hagenaars, T. J., Lugnér, A. K., and Wallinga, J. (2008). Optimal allocation of pandemic influenza vaccine depends on age, risk and timing. *Vaccine*, 26(29-30):3742–3749.

NCC (2021). Lebanon national deployment and vaccination plan for covid-19 vaccines, 28 january 2021. Technical report, Republic of Lebanon, Ministry of Public Health.

Nering Bögel, M. (2020). Modelling covid-19 in refugee settlements. Retrieved on March 3rd, 2021 on: https://github.com/MeykeNB/Covid-19-in-refugee-camps.

of Sciences, N. A. (2020). Framework for equitable allocation of covid-19 vaccine.

Oh, S. (2017). Surveillance and control: The encampment and biometric identification of rohingya refugees in bangladesh. *Perspective*, 93.

Oka, R. (2011). Unlikely cities in the desert: The informal economy as causal agent for permanent" urban" sustainability in kakuma refugee camp, kenya. *Urban Anthropology and Studies of Cultural Systems and World Economic Development*, pages 223–262.

Omata, N. and Kaplan, J. D. (2013). *Refugee livelihoods in Kampala, Nakivale and Kyangwali refugee settlements: Patterns of engagement with the private sector*. Refugee Studies Centre, Oxford Department of International Development . . . .

Patel, R., Longini Jr, I. M., and Halloran, M. E. (2005). Finding optimal vaccination strategies for pandemic influenza using genetic algorithms. *Journal of theoretical biology*, 234(2):201–212.

Peiris, M. and Leung, G. M. (2020a). What can we expect from first-generation covid-19 vaccines? *The Lancet*, 396(10261):1467–1469.

Peiris, M. and Leung, G. M. (2020b). What can we expect from first-generation covid-19 vaccines? *Lancet (London, England)*, 396(10261):1467–1469.

Pellecchia, U., Crestani, R., Decroo, T., Van den Bergh, R., and Al-Kourdi, Y. (2015). Social consequences of ebola containment measures in liberia. *PloS one*, 10(12):e0143036.

Population of the World (2021). Population of bangladesh. Retrieved on April 7th, 2021 on: https://www.livepopulation.com/country/bangladesh.html.

Porter, G., Hampshire, K., Kyei, P., Adjaloo, M., Rapoo, G., and Kilpatrick, K. (2008). Linkages between livelihood opportunities and refugee–host relations: learning from the experiences of liberian camp-based refugees in ghana. *Journal of refugee studies*, 21(2):230–252.

Privett, N. and Gonsalvez, D. (2014). The top ten global health supply chain issues: perspectives from the field. *Operations Research for Health Care*, 3(4):226–230.

Rahman, M. R. and Islam, K. (2019). Massive diphtheria outbreak among rohingya refugees: lessons learnt. *Journal of travel medicine*, 26(1):tay122.

Rajabi, M., Pilesjö, P., Shirzadi, M. R., Fadaei, R., and Mansourian, A. (2016). A spatially explicit agent-based modeling approach for the spread of cutaneous leishmaniasis disease in central iran, isfahan. *Environmental modelling & software*, 82:330–346.

Rieger, J. et al. (2020). Navigating at the margins: Family, mobility and livelihoods amongst rohingya refugees in bangladesh.

Rohingya Camp Map (2018). Cxb map. data retrieved from https://www.google.com/maps/d/u/0/viewer?hl=ko&ll=21.158414645026422%2C92.1561152766042&z=16&mid=1oGmkWn3XuiA8K-eSPkLq5K8Zyeo.

Rosenbach, G., Tiburcio, E., Filipski, M., Dorosh, P., Sen, B., et al. (2018). *Economic activities of forcibly displaced populations: An analysis of enterprises in Southern Bangladesh*. International Food Policy Research Institute.

Sakamoto, M., Begum, S., and Ahmed, T. (2020). Vulnerabilities to covid-19 in bangladesh and a reconsideration of sustainable development goals. *Sustainability*, 12(13):5296.

Shammi, M., Robi, M. R., and Tareq, S. M. (2020). Covid-19: socio-environmental challenges of rohingya refugees in bangladesh. *Journal of Environmental Health Science and Engineering*, 18(2):1709–1711.

Sharma, O., Sultan, A. A., Ding, H., and Triggle, C. R. (2020). A review of the progress and challenges of developing a vaccine for covid-19. *Frontiers in immunology*, 11:2413.

Shim, E. (2021). Optimal allocation of the limited covid-19 vaccine supply in south korea. *Journal of clinical medicine*, 10(4):591.

Shokri, A., Sabzevari, S., and Hashemi, S. A. (2020). Impacts of flood on health of iranian population: Infectious diseases with an emphasis on parasitic infections. *Parasite epidemiology and control*, 9:e00144.

Silva, P. C., Batista, P. V., Lima, H. S., Alves, M. A., Guimarães, F. G., and Silva, R. C. (2020). Covid-abs: An agent-based model of covid-19 epidemic to simulate health and economic effects of social distancing interventions. *Chaos, Solitons & Fractals*, 139:110088.

Singh, J. and Singh, J. (2020). Covid-19 and its impact on society. *Electronic Research Journal of Social Sciences and Humanities*, 2.

Snowdon, G. (2020). Bringing greater economic opportunities for the host community, wfp reopens farmers' markets in rohingya camps. Retrieved on March 18th, 2021 on: https://www.wfp.org/news/bringing-greater-economic-opportunities-host-community-wfp-reopens-farmers-markets-rohingya.

Stadnytskyi, V., Anfinrud, P., and Bax, A. (2021). Breathing, speaking, coughing or sneezing: What drives transmission of sars-cov-2? *Journal of Internal Medicine*.

Stokel-Walker, C. (2021). What we know about covid-19 reinfection so far. *bmj*, 372.

Swan, D. A., Bracis, C., Janes, H., Moore, M., Matrajt, L., Reeves, D. B., Burns, E., Donnell, D., Cohen, M. S., Schiffer, J. T., et al. (2021). Covid-19 vaccines that reduce symptoms but do not block infection need higher coverage and faster rollout to achieve population impact. *Scientific Reports*, 11(1):1–9.

Talukder, S. R. (2021). Will vaccine nationalism lead to the exclusion of rohingya refugees? Retrieved on February 1st, 2021 on: http://www.ipsnews.net/2021/01/will-vaccine-nationalism-lead-exclusion-rohingya-refugees/.

Tanner, M. W., Sattenspiel, L., and Ntaimo, L. (2008). Finding optimal vaccination strategies under parameter uncertainty using stochastic programming. *Mathematical biosciences*, 215(2):144–151.

Tay, A., Riley, A., Islam, R., Welton-Mitchell, C., Duchesne, B., Waters, V., Varner, A., Moussa, B., Alam, A. M., Elshazly, M., et al. (2019). The culture, mental health and psychosocial wellbeing of rohingya refugees: a systematic review. *Epidemiology and psychiatric sciences*, 28(5):489–494.

Taylor, J. E., Filipski, M. J., Alloush, M., Gupta, A., Valdes, R. I. R., and Gonzalez-Estrada, E. (2016). Economic impact of refugees. *Proceedings of the National Academy of Sciences*, 113(27):7449–7453.

Thacker, B. H., Doebling, S. W., Hemez, F. M., Anderson, M. C., Pepin, J. E., and Rodriguez, E. A. (2004). Concepts of model verification and validation.

Thul, L. and Powell, W. (2021). Stochastic optimization for vaccine and testing kit allocation for the covid-19 pandemic. *arXiv preprint arXiv:2101.01204*.

Torres, D. d. A., Ribeiro, L. d. C. B., Riello, A. P. d. F. L., Horovitz, D. D. G., Pinto, L. F. R., and Croda, J. (2020). Reinfection of covid-19 after 3 months with a distinct and more aggressive clinical presentation: Case report. *Journal of medical virology*.

Truelove, S., Abrahim, O., Altare, C., Lauer, S. A., Grantz, K. H., Azman, A. S., and Spiegel, P. (2020). The potential impact of covid-19 in refugee camps in bangladesh and beyond: a modeling study. *PLoS medicine*, 17(6):e1003144.

Tuite, A. R., Fisman, D. N., Kwong, J. C., and Greer, A. L. (2010). Optimal pandemic influenza vaccine allocation strategies for the canadian population. *PloS one*, 5(5):e10520.

Tuite, A. R., Zhu, L., Fisman, D. N., and Salomon, J. A. (2021). Alternative dose allocation strategies to increase benefits from constrained covid-19 vaccine supply. *Annals of internal medicine*.

Ullah, A. A. (2011). Rohingya refugees to bangladesh: Historical exclusions and contemporary marginalization. *Journal of Immigrant & Refugee Studies*, 9(2):139–161.

Ullah, A. A., Hossain, M. A., and Chattoraj, D. (2020). Covid-19 and rohingya refugee camps in bangladesh. *Intellectual Discourse*, 28(2):793–806.

UNHCR (2011). Unhcr-ngo toolkit for practical cooperation on resettlement. community outreach - outreach to host communities: Definitions and faqs. Retrieved on March 15th, 2021 on: https://www.unhcr.org/protection/resettlement/4cd7d1509/unhcr-ngo-toolkit-practical-cooperation-resettlement-community-outreach.html?query=definitions.

UNHCR (2020a). Covid-19: Emerging practices on livelihoods and economic inclusion. Retrieved on February 4th, 2021 on: https://www.unhcr.org/publications/brochures/5ecfacab4/covid-19-emerging-practices-livelihoods-economic-inclusion.html publisher = UNHCR.

UNHCR (2020b). Joint multi-sector needs assessment (j-msna) bangladesh rohingya refugees (july - august 2020).

UNHCR (2020c). Livelihoods and economic inclusion. Retrieved on January 28th, 2021 on: https://www.unhcr.org/livelihoods.html.

UNHCR (2020d). Refugee camps. Retrieved on January 28th, 2021 on: https://www.unrefugees.org/refugee-facts/camps/.

UNHCR (2020e). Rohingya emergency. Retrieved on January 29th, 2021 on: https://www.unhcr.org/rohingya-emergency.html.

UNHCR (2021). Refugee data finder. Retrieved on January 28th, 2021 on: https://www.unhcr.org/refugee-statistics/.

UNHCR (2021a). Refugees and the impact of covid-19. Technical report, UNHCR.

UNHCR (2021b). Unhcr urges stronger support for refugee vaccinations in asia. Retrieved on June 26th, 2021 on: https://www.unhcr.org/news/briefing/2021/6/60b5ede64/unhcr-urges-stronger-support-refugee-vaccinations-asia.html.

United Nations (2016). *Sustainable development goals report 2016*. UN.

Van Dam, K. H., Nikolic, I., and Lukszo, Z. (2012). *Agent-based modelling of socio-technical systems*, volume 9. Springer Science & Business Media.

Vermund, S. H. and Pitzer, V. E. (2021). Asymptomatic transmission and the infection fatality risk for covid-19: Implications for school reopening. *Clinical Infectious Diseases*, 72(9):1493–1496.

Vonen, H. D., Olsen, M. L., Eriksen, S. S., Jervelund, S. S., and Eikemo, T. A. (2020). Refugee camps and covid-19: Can we prevent a humanitarian crisis? *Scandinavian Journal of Public Health*, page 1403494820934952.

Wallinga, J., van Boven, M., and Lipsitch, M. (2010). Optimizing infectious disease interventions during an emerging epidemic. *Proceedings of the National Academy of Sciences*, 107(2):923–928.

Werker, E. (2007). Refugee camp economies. *Journal of Refugee Studies*, 20(3):461–480.

West, J., Everden, S., and Nikitas, N. (2021). A case of covid-19 reinfection in the uk. *Clinical Medicine*, 21(1):e52.

Whitaker, B. E. (1999). *Changing opportunities: refugees and host communities in Western Tanzania*. Centre for Documentation and Research, United Nations High Commissioner for . . . .

WHO (2020a). Covax. working for global equitable access to covid-19 vaccines. Retrieved on March 25th, 2021 on: https://www.who.int/initiatives/act-accelerator/covax.

WHO (2020b). Who concept for fair access and equitable allocation of covid-19 health products.

World Health Organization (2021). Covid-19 national deployment and vaccination plan: submission and review process, 29 january 2021. Technical report, World Health Organization.

World Health Organization et al. (2020). Who sage values framework for the allocation and prioritization of covid-19 vaccination, 14 september 2020. Technical report, World Health Organization.

Wright, A. L., Sonin, K., Driscoll, J., and Wilson, J. (2020). Poverty and economic dislocation reduce compliance with covid-19 shelter-in-place protocols. *Journal of Economic Behavior & Organization*, 180:544–554.

Wu, C. J. and Hamada, M. S. (2011). *Experiments: planning, analysis, and optimization*, volume 552. John Wiley & Sons.

Wu, J. T., Riley, S., and Leung, G. M. (2007). Spatial considerations for the allocation of pre-pandemic influenza vaccination in the united states. *Proceedings of the Royal Society B: Biological Sciences*, 274(1627):2811–2817.

Wu, Y.-C., Chen, C.-S., and Chan, Y.-J. (2020). The outbreak of covid-19: An overview. *Journal of the Chinese Medical Association*, 83(3):217.

Xu, J., Gao, Y., and Madey, G. (2003). A docking experiment: Swarm and repast for social network modeling. In *Seventh Annual Swarm Researchers Meeting (Swarm2003)*, pages 1–9.

Yamin, D. and Gavious, A. (2013). Incentives' effect in influenza vaccination policy. *Management Science*, 59(12):2667–2686.

Yesmin, S. (2016). Policy towards rohingya refugees: a comparative analysis of bangladesh, malaysia and thailand. *Journal of the Asiatic Society of Bangladesh (Hum.)*, 61(1):71–100.

Zakaria, F. and Shanmugaratnam, N. (2003). Moving into the extra household domain: Survival strategies of displaced muslim women in sri lanka. *In the maze of displacement: Conflict, Migration and Change, Oslo: Norwegian Academic Press*.

Zetter, R. and Ruaudel, H. (2016). Refugees' right to work and access to labor markets–an assessment. *World Bank Global Program on Forced Displacement (GPFD) and the Global Knowledge Partnership on Migration and Development (KNOMAD) Thematic Working Group on Forced Migration. KNOMAD Working Paper. Washington, DC: World Bank Group*.

A RESEARCH PLANNING

A.1 RESEARCH FLOW DIAGRAM

A Research Flow Diagram is presented in figure A.1. This diagram is a visually summarized the integration of the research approaches and methods defined in this chapter 3. For each sub-question is shown what data is needed to answer this question, and how this information is used to answer the following sub-question. In this way, the diagram presents a structural and sequential research process flow. As a result, the main research question can be answered in the final phase in the diagram.

A.2 TIME SCHEDULE

Figure A.2 presents a time schedule which has been followed to conduct this research. This figure describes an step-wise overview on how this research will be conducted over a six-month time period.

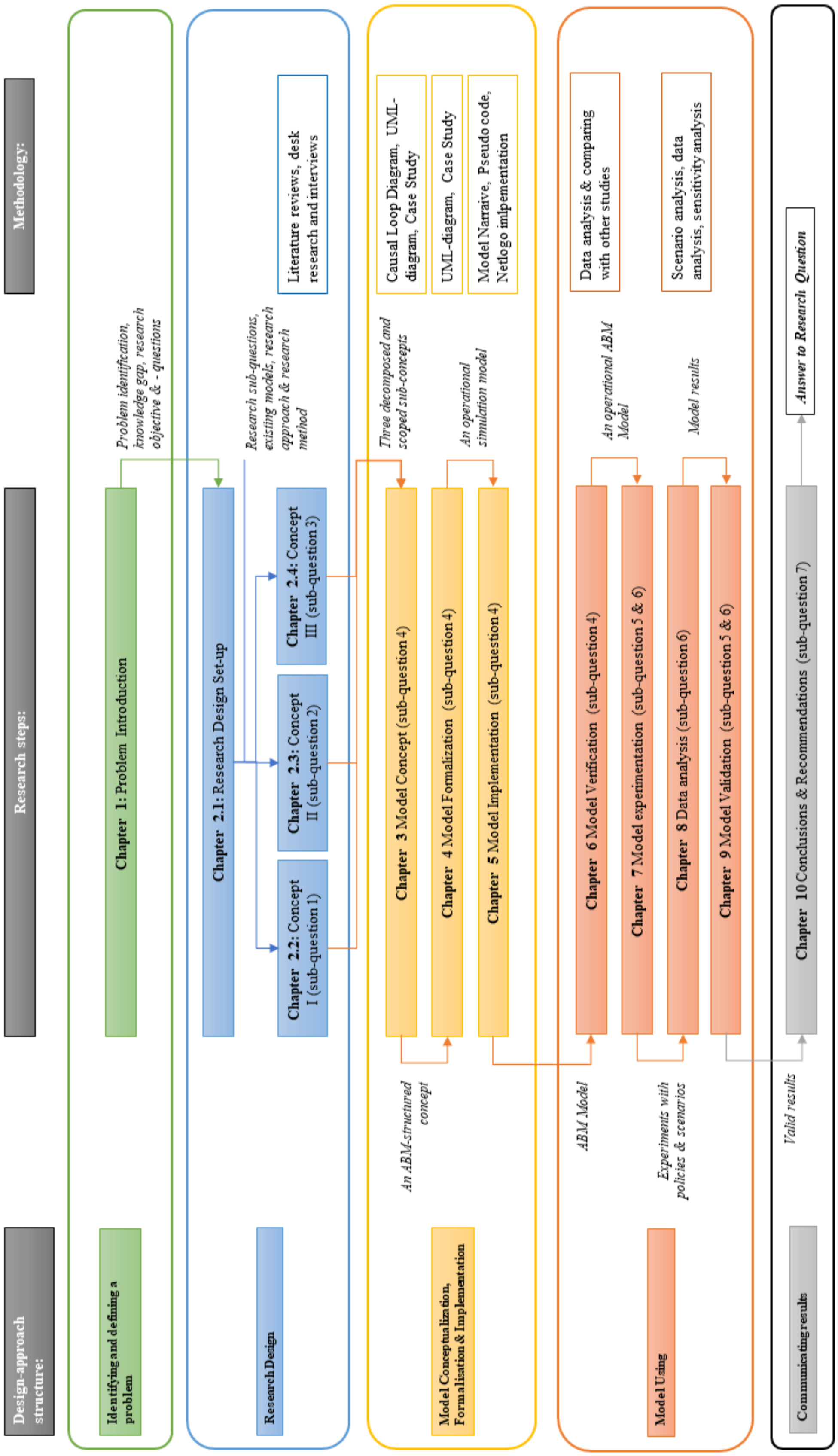


Figure A.1: Research Flow Diagram

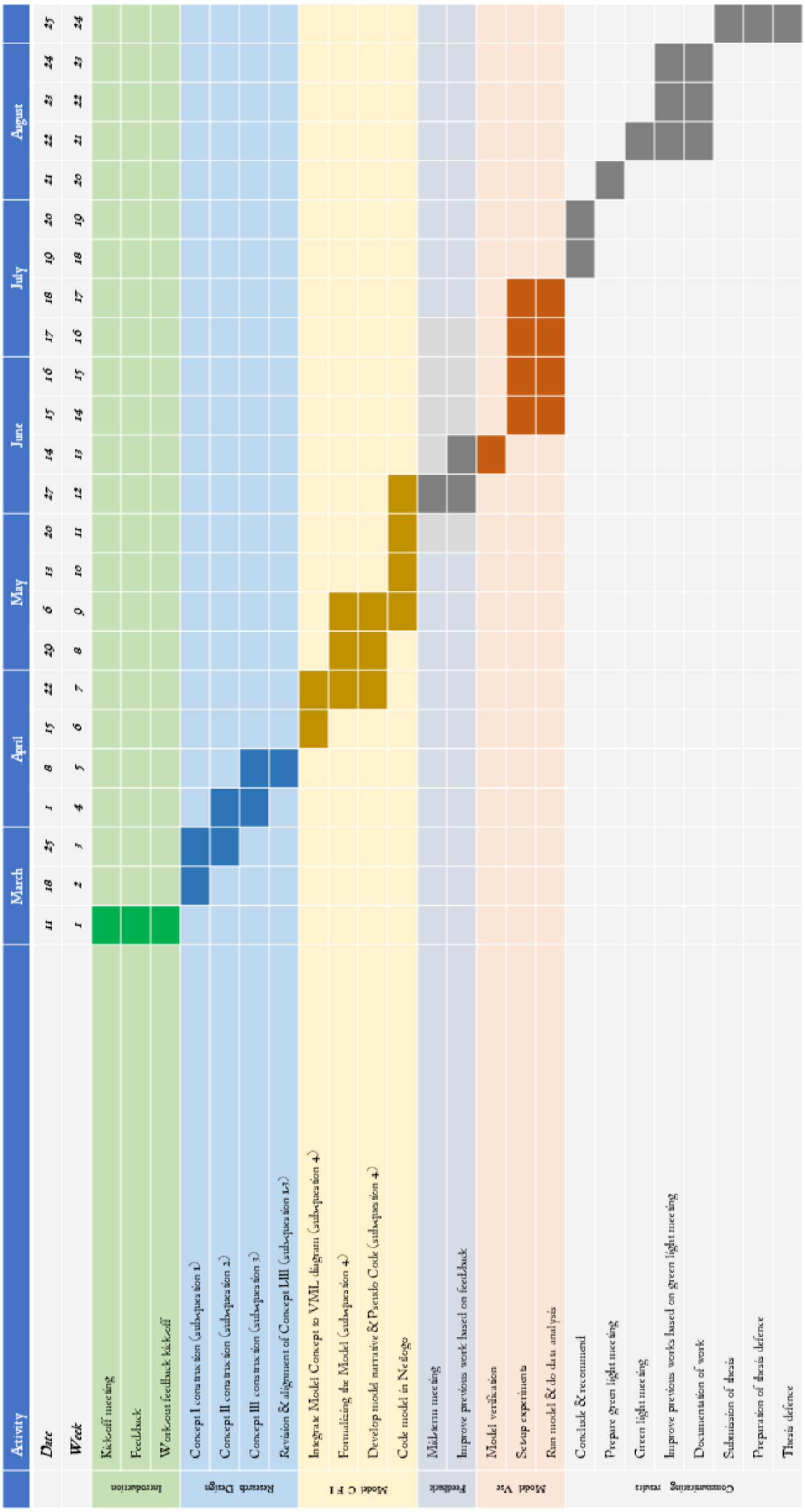


Figure A.2: Time Schedule

B INTERVIEWS

Three interviews were conducted (from the 29th of March - the 1st of April 2021) with experts from UNHCR, working on the Rohingya response in general and on the COVID-19 response. To these interviewees, questions were asked in a semi-structured manner. As a general basis for each interview, the interviewees were sent questions on three topics, as presented in section B.1. They were allowed to answer these questions freely and with the option to add things. Section B.2-B.4 present an overview of the insights from these interviews per topic. These are used in this research for creating a more defined context of the Rohingya camp settlements, the impact of COVID-19 and for structuring and validating the model used for this research. For more information on the background of the interviewees, who requested to remain anonymous, contact the author of this research.

B.1 INTERVIEW QUESTIONS

- Topic 1: Daily lives of Rohingyas interacting with the host community
  - Did the Rohingyas interact with the local Bangladeshi before COVID-19? If yes, how, why and where do they do it roughly? And how many times per week/day? An indication is enough.
  - Is a Rohingya camp block/settlement open for other people? And do the Rohingyas without official refugee status leave the camps?
  - What does a normal day (without COVID-19) look like for a Rohingya refugee, expressed in an activity schedule? (E.g.: what does an average Rohingya refugee do when he/she wakes up until he/she goes to bed?)
  - What is a normal living area for a refugee? Does he/she only live in a sub-block and never leave it? Or do they live inside the camp blocks? Or do they move constantly from their own blocks to other blocks?
- Topic 2: Impact of COVID-19 on refugee camps
  - How did COVID-19 and the following measures affect the interactions between Rohingyas with other Rohingyas and between Rohingyas and the host community?
  - I read the Rohingya settlements were in lockdown for a time period of weeks. How did that express in reality? Did they still leave the camps or did they behave according to the rules?
  - What changed physically/geographically to the camp settlements since COVID-19 started, which limited the Rohingya's ability to move inside their camp blocks and out of the camp blocks?
- Topic 3: Vaccines in Rohingya refugee camps
  - What's your experience on other vaccines than COVID-19 vaccines for Rohingyas?
  - Do you consider COVID-19 vaccines an important factor in bringing back a normal life in refugee camp settlements?
  - As COVID-19 mostly harms older people and vulnerable people, the health-related impact of COVID-19 will most likely be low. Do you think this affects the vaccination strategy on whom to prioritize to vaccinate first?

B.2 INTERVIEW 1

B.2.1 Interview Details

- **Date**: 29th of March, 2021
- **Name of interviewee:** Anonymous, please contact author for verification
- **Expertise:** Senior Public Health Officer - Regional Bureau for Asia and Pacific

B.2.2 Topic 1: Interactions of Rohingyas and host communities

A. Main motives for interactions:

- Markets: Most of the interactions between Rohingyas and host communities happen in trading centres and the markets, inside and on boundaries of the camps.
  - Here, people from the host community come in with supplies. An estimated 30% of the Rohingyas go to these markets, buying these goods from the host community people, which they use or later on sell other Rohingyas.
  - The further you go out of the camps, the less interactions takes place, for the reason that more check points filter out informal refugees (with no status).
  - On the markets, social interactions between the Rohingyas and host communities also centre around phone charging hubs. Here, both meet and discuss the news.
  - Work is available formally on the markets as traders from the host communities are allowed to set up businesses in the camps, to access livelihoods
- Health care facilities: people from the host community enter the camps if they work in healthcare facilities in the camps. As the healthcare facilities are owned by the government, this is where the formally working host communities can execute a job
- Education: teachers at schools are also from host communities work formally.
- Religious: In mosques, they also meet both. The Maji & Imams have a great influence here to spread knowledge on the COVID-19 situation and on vaccines. In the mosques, the people are mainly Rohingyas. But the Bangladeshi are also Muslim, so the ones who live close also come here.

B. Openness of Rohingya camp sites:

- Nothing has embarked the camps, so everyone can go in and out without any restrictions. However, still main entry point exists which are used as they are most easy to use.
- Formally, there are limitations. But in practice, the limitations are zero.
- Rohingyas go out whenever they want to go out. There are no real restrictions. But most of the Rohingyas will stay inside the camps.
- There are no fences around the camps, and the ones which were built in May 2020 after the first COVID-19 cases started were not finished.

C. Daily activities of Rohingyas & host communities

- Rohingyas and host communities wake up
- Rohingyas and host communities visit a mosque five times a day, for praying: twice in the morning, once in the afternoon, twice in the night. There are several mosques, for 150.000 Rohingyas, 1 mosque. Mosques are mostly man, no women. 90-95% of mosque visitors is men.

- After that, the adults and elderly both go to the market areas ("It's always packed"). People are hanging around here on the streets for an estimated 3/4 hours. These are big, open air markets.
- Children go to schools inside the camps but can have host community teachers.

D. Geographical living area of Rohingyas

- Interaction is quite communal, so they interact mainly through the sub-blocks and on the places like marketplaces and trading centres.
- They can easily go out of their camp areas. Within camps, there are no real borders. Only the Tekhnaf area is quite isolated, so here no interactions from that camp to others takes place here. "From camp 1, they can go to a health-facility in camp 10."
- They move around from sub-blocks to other sub-blocks

B.2.3 Topic 2: Impact COVID-19 on the Rohingya Camp Settlements

- The first lockdown was really strict, for both hosts and Rohingyas. It meant: intra-camp movements were limited, camps were isolated and healthcare workers could not go into the camps.
- They would not go to mosques for around 2/3 months
- They would not go to markets as they were close for around 2/3 months
- After the lockdown, inside the camps did not have a lot of restrictions. They were still isolated from outside
- There is no social distancing in the Cox Bazar region anymore. Only in the initial phase.
- After the first strict lockdown, the life returned back to normal as restricting measures were eased by two degrees:
  - By an estimated 60%: with mosques opened for limited numbers of people and markets open, but closed schools for kids
  - By estimated 80%: with mosques opened for limited numbers of people and markets open, but open schools for kids
- Most non-pharmaceutical measures which are proven to be most effective are wearing face masks and using sanitation facilities
- Current situation in the camps: in the camp, no social distancing is done. Masks are promoted, with approximately 30-40% compliance to wear it, mainly centred around the health facilities. Schools open and close depending on the government's decisions. Mosques opened again.
- After the highest levels of fear were gone, most of the host community reached out to the camps again.
- Prevalence is estimated around 60%, which is not published officially. There was a high spread inside the camps, but they just didn't have severe cases. A reason for that is the fact demographic characteristics are different: the population is not that old.
- Sometimes the Rohingyas hide their results, if this threatens their existence. At some point, testing costed money, so testing lost its momentum.

B.2.4 Topic 3: The Vaccination Strategy in Bangladesh

- Vaccine strategies for Bangladesh are constantly changing.
- The main strategy in Bangladesh follows the line of the generally (worldwide) supported vaccine programs: first, healthcare workers are provided vaccines, then other essential workers and the elderly.
- Inside the camps, people ¿ 40 years old are vaccinated first, which is done as demographic differences exist and the population of the Rohingyas is younger.
  - From March 2021, 130.000/150.000 vaccines (à 30% of the Rohingya population) will be distributed over these people, which should be okay considering healthcare capacities and deaths.
  - 40 million doses are needed in Bld. 10 million were provided in the first batch, of which 150.000 were reserved for the Rohingyas.
  - Interviewee thinks will be 150.000 for the second batch, with intervals of around 8 weeks
- Issues are still at stake with the supply of the vaccines. As there are issues, they have shifted with the focus of the first batch to the local Bangladeshi.
- They receive AstraZeneca, CoviShield (from India)
- The first priority is health, as that also allows for more socioeconomic freedom in the end, as the Government sees the health facilities are not out of capacity.
- Socioeconomic reasons are most important: markets can open up, normal life can return back to normal more easy.
- A second reason is the Rohingyas are still considered to return back to Myanmar. Vaccines can allow them to go back more easily.

B.3 INTERVIEW 2

B.3.1 Interview Details

- **Date**: 31st of March, 2021
- **Name of interviewee:** Anonymous, please contact author for verification
- **Expertise:** Livelihoods Officer in Cox's Bazar, Bangladesh

B.3.2 Topic 1: Interactions of Rohingyas and host communities

A. Main motives for interactions:

- An estimated 35-40% of the Rohingyas interact with the host community in general.
- Markets: Most of the interactions between Rohingyas and host communities happen in the vicinity markets, on the camp boundaries
  - Markets are big, shared places, located around the roads. For example, the Kutupalong, Balukhali, Palongkhali market. Here, an estimated 10.000 people visit a day, people staying an estimated time of 1 hour, and gender and age is pretty mixed.
  - After this, the Rohingyas sell products to other Rohingyas inside the camps
  - Some Rohingyas have a small shops in front of their shelter. Here, no interaction is recognized with the host community.

- Volunteers from host communities go into the camps. These are 35.000 in total, of which 20-25% is host community, and before COVID-19 15.000 vulunteers a day would enter the camps on a daily basis. Since COVID-19, around 50% dropped. Volunteers are:
  - Health care workers inside the camps from the host community
  - Teachers from the host community teachers come to schools.
  - Other volunteers also come to the camps to work on different things.
  - Here, an estimated 20% of 15.000 volunteers entering the camps on a daily basis comes from the host community
  - Religious: Both gather in mosques, as both populations are Muslim. Inside camps, you have a mosque for each sub-block. Also, some mosques close to the camps exist, where they mix with host communities. This is an estimated 20% Rohingyas. This depends on how far it is. Mosques are close to the big markets

B. Openness of Rohingya camp sites:

- In agricultural peak seasons, Rohingyas leave to work in agriculture
- In the past, it was really easy to go in and out.

C. Daily activities of Rohingyas & host communities

- Rohingya:
  - Early wake-up
  - 8:00: First, they go out to reach for food
  - 9:30-10: Men leave to work
  - 9:30-10: Women go to women-friendly centres, where they can learn. During COVID-19, children came along.
  - 10:00: All people are in
  - 15-16:00: Most of the people come back, and do not go out again. For working people, they depend it on how much they have earned. Some women go out to the women-friendly centre again.
  - 17:30: Everyone back home, as it is dark and facilities close. Here, sometimes crime happens.
- Host community:
  - 8:30-9:00: People start entering the camp on a normal day
  - 10:00: All people are in
  - 15:00: First people start leaving
  - 17:00: Most people leave
  - 17:30: Everyone left, as they are obliged to leave at 5:30

D. Geographical living area of Rohingyas

- Camp boundaries are vague for the people in the camps.
- Blocks are named by a letter
- The Rohingyas go beyond the blocks, and sometimes also go to other camps.
- Every block has a mosque
- A block hosts around 2000 people on average.

B.3.3 Topic 2: Impact COVID-19 on the Rohingya Camp Settlements

- On markets, interactions were cut by 50% on the big markets. This means, 5000 visitors on the markets, which are still mixed between host-communities and Rohingyas.

- There are official entry points. Now, fences are built around the camps, not allowing the people to go in or out easily. Host communities do not come into the camps. These are restrictions introduced by the government. Interactions dropped by an estimated 50%.

- When Rohingyas tell the officials they are leaving the camp for visiting a market, they are sometimes allowed.

- Imams and Mahjis have an important role in communication

- Different measures were implemented with different impacts on interactions:
  - Strict lockdown: in march 2020, host-refugee interaction was down by 80% for 4 months. In general, refugee-refugee interactions dropped by 50%.
  - Soft strict lockdown: After 4 months, host-refugee interaction was down for 30% after 3 or 4 months. Here, more activities were allowed like livelihood activity (if wearing a face mask), shelter activities.
  - Now, new restrictions are introduced, so host-refugee interactions are down by 50-60% again. Refugee-refugee interactions are quite normal.

- Isolation: there were isolation centres raised after COVID-19 started. These can host up to 6000 people. People were and are quite compliant to go here with symptoms.

- Masks are mandatory, but not everyone wears it.

- Cases in the camps were quite low, but the reason for this is not really clear.

B.3.4 Topic 3: The Vaccination Strategy in Bangladesh

- Trust was very low in the beginning. After a week, it went up, but after 5 weeks it went down again. Namely, AstraZeneca is from India, which is a conflicting region for Bangladeshi.

- The program has not started yet. It was planned for the 27th of March, but Bangladesh vaccine supplies are in a crisis now. Bangladesh receives 11 million doses from COVAX.

- The reason to vaccinate people above 40 years old is based on the government, noticing this group is most in need to be given priority.

- Also frontline workers are prioritized.

B.4 INTERVIEW 3

B.4.1 Interview Details

- **Date:** 14th of June, 2021

- **Name of interviewee:** Anonymous, please contact author for verification

- **Expertise:** Healthcare worker & economist at Cox's Bazar (Bangladesh) in the Rohingya camps

B.4.2 Topic 1: Validation of outcomes base model

- It is really hard to estimate the current number of infections inside the camp, which is therefore hard to validate with data. In October, a zero-prevalence study will come out which allows to further validate the number of currently infected people.
- One of the less valid parts of model is the frequency of visitations of household members to the markets. As the people trade very small products, they will likely visit markets more often.
- The division of an unconditional and a conditional lockdown is practically impossible. According to the current practices in the camp, only a conditional lockdown is imposed which can vary over time.
- Regarding the conditional lockdown, it is more likely infections will be lower in practice, than for the estimation which is made in this study.
- A reason why your infection estimations could be compensated with the less valid infections resulting from a conditional lockdown is the fact a lot of infections go unregistered and are not known. This is due to limited (willingness of) testing
- Going to mosques is not inside, but mainly happens outside the mosque since COVID-19 started. Therefore, your assumption of even infection forces for this typical 'indoor' activity is correct and a valid assumption.
- Compliance is not really easy to measure. Up to now, some measurements have been done by random assessments in the camp, which showed low compliance for younger people to wear a mask. In general, it is estimated below 40%.
- Compliance is higher for stay-at-home measures, which this research also indicates. This is due to the fact isolation is mandatory in case of a positive COVID-19 test result.

B.4.3 Topic 2: Validation of outcomes on vaccine allocation strategies

- The expert could not say much about the effectiveness of the delivery of vaccines to the Rohingyas
- What he could say was, the first age-group is now vaccinated, which is the age-group above 55 years.
- The main problem with the vaccines is vaccine scarcity. Vaccine scarcity is especially high since May 2021, since the supply of vaccines from India was blocked.

C VACCINE ALLOCATION STRATEGIES IN OTHER COUNTRIES

C.1 THE WHO SAGE VALUES FRAMEWORK

The WHO published the SAGE Values Framework for *the equitable protection and promotion of human well-being among all people of the world* [World Health Organization et al., 2020, p.4]. This framework is shown in figure C.1

Goal Statement	COVID-19 vaccines must be a global public good. The overarching goal is for COVID-19 vaccines to contribute significantly to the equitable protection and promotion of human well-being among all people of the world.
Principles	**Objectives**
Human Well-Being	Reduce deaths and disease burden from the COVID-19 pandemic;
	Reduce societal and economic disruption by containing transmission, reducing severe disease and death, or a combination of these strategies;
	Protect the continuing functioning of essential services, including health services.
Equal Respect	Treat the interests of all individuals and groups with equal consideration as allocation and priority-setting decisions are being taken and implemented;
	Offer a meaningful opportunity to be vaccinated to all individuals and groups who qualify under prioritization criteria.
Global Equity	Ensure that vaccine allocation takes into account the special epidemic risks and needs of all countries; particularly low-and middle-income countries;
	Ensure that all countries commit to meeting the needs of people living in countries that cannot secure vaccine for their populations on their own, particularly low- and middle-income countries.
National Equity	Ensure that vaccine prioritization within countries takes into account the vulnerabilities, risks and needs of groups who, because of underlying societal, geographic or biomedical factors, are at risk of experiencing greater burdens from the COVID-19 pandemic;
	Develop the immunization delivery systems and infrastructure required to ensure COVID-19 vaccines access to priority populations and take proactive action to ensure equal access to everyone who qualifies under a priority group, particularly socially disadvantaged populations.
Reciprocity	Protect those who bear significant additional risks and burdens of COVID-19 to safeguard the welfare of others, including health and other essential workers.
Legitimacy	Engage all countries in a transparent consultation process for determining what scientific, public health, and values criteria should be used to make decisions about vaccine allocation between countries;
	Employ best available scientific evidence, expertise, and significant engagement with relevant stakeholders for vaccine prioritization between various groups within each country, using transparent, accountable, unbiased processes, to engender deserved trust in prioritization decisions.

Figure C.1: The WHO SAGE Values Framework [World Health Organization et al., 2020, p.4]

C.2 VACCINE PRIORITIZATION IN LEBANON

The Lebanon Ministry of Public Health (MOPH) published the estimated priority populations for COVID-19 vaccination in January 2021 in the Lebanon NDVP. This prioritization strategy is shown in figure C.2.

Phase	Target population	Population size[1]	Share of population*
First 35%[2]	High risk health workers	55,000	0.8%
	Aged 65 and older	600,143	9.2%
	Those below age 65 (55 – 64 years) but with comorbidities	237,183	3.6%
	All those between ages 55-64 not covered earlier, 16-54 years with co-morbidities[3], health workers not covered earlier	237,183 1,150,671 5,000	3.6% 17.7% 0.1%
	Persons and staff in elderly shelters, prisons, and individuals essential for preserving the essential function of the society (the national COVID-19 vaccination committee will define strict criteria to identify recipients of the latter group).	25,000	3.4%
Next 35%	Other vulnerable populations, schoolteachers and school staff**, childcare workers, other critical workers in high risk settings, remaining health care workers, family caregivers of those age ≥65 or with special needs, and all those above the age of 16 willing to be vaccinated	2,449,820	35%

Figure C.2: Prioritization of COVID-19 vaccines in Lebanon [NCC, 2021, p.23]

C.3 VACCINE PRIORITIZATION OF ROHINGYA POPULATION IN BANGLADESH

The Government of Bangladesh has included the Rohingya refugee population in their NDVP. Here, the aim is to include the Rohingyas with a health-related high-risk profile first. Their prioritization strategy is shown in figure C.3.

Prioritization	Phases and Stages	Number of beneficiaries
Frontline health workers (≥18 years) and prioritized population (≥40 years)	Phase 1- Stage A	129,698
Between the age of 18-39years*	Phase 1 - Stage B	272,070
Below the age of 18 years*	Phase 2	272,652
Pregnant Women*	Phase 3	19,816

Figure C.3: Prioritization of COVID-19 vaccines in Bangladesh [Government of Bangladesh et al., 2021, p.14]

D CONCEPTUALIZATION & FORMALIZATION

D.1 CONCEPTUALIZATION

D.1.1 Concept I: Conceptualization of agent interactions (part I)

Figure D.1 shows the conceptualization of refugee-host interactions which is used in this research.

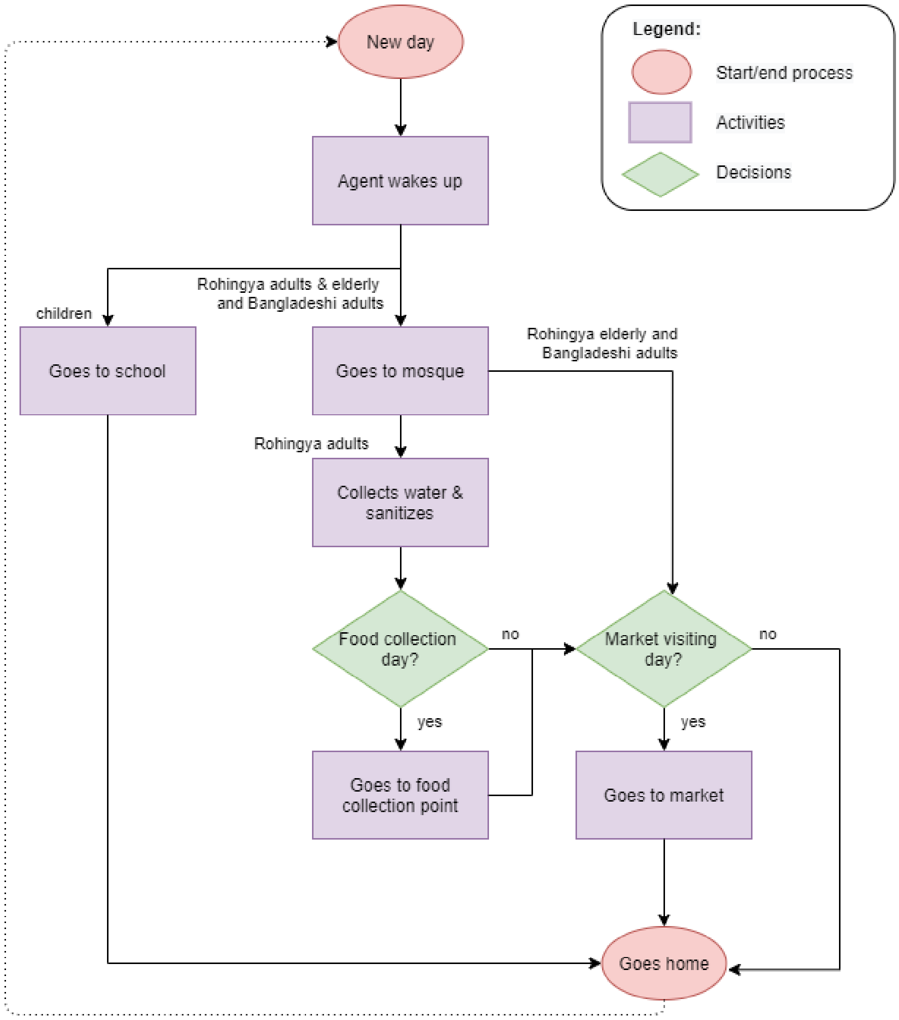


Figure D.1: Agent behavior based on daily activities

D.1.2 Concept II: Conceptualization of restricting COVID-19 measures

Figure D.2 shows the conceptualization of the restricting COVID-19 measures which is used in this research.

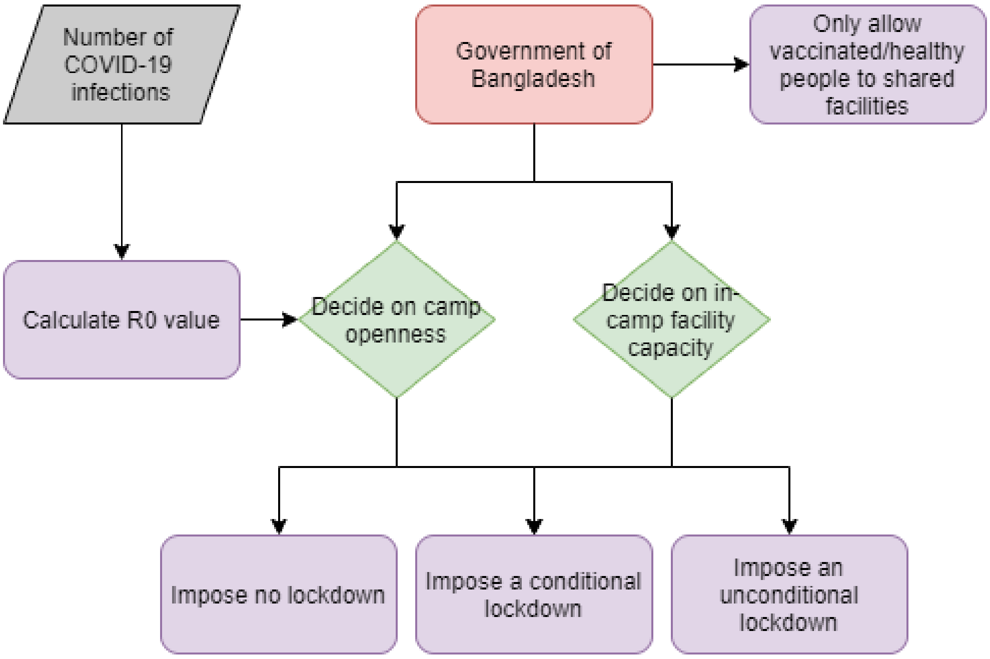


Figure D.2: Sub-concept 2 for restricting COVID-19 measuress

D.1.3 Concept III: Conceptualization of vaccine allocation

Figure D.3 shows the conceptualization of the concept of vaccine allocation as it is used in this research.

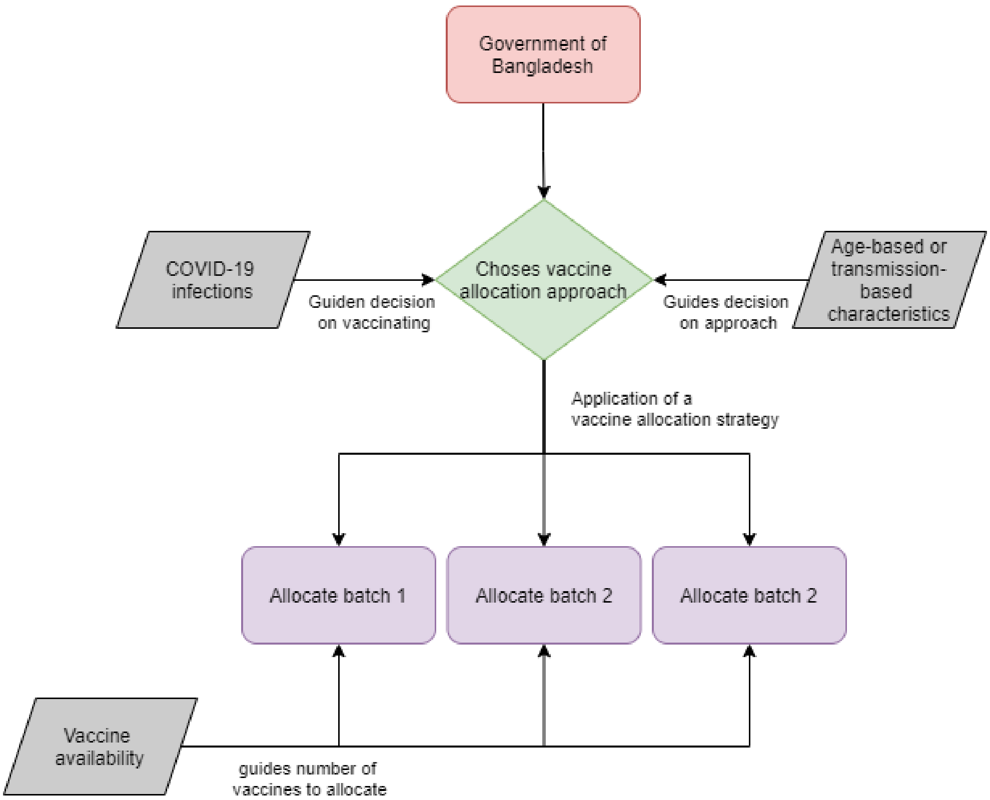


Figure D.3: Sub-concept of vaccine allocation mechanism

D.1.4 Concept IV: Conceptualization of a COVID-19 transmission model

Figure D.4 shows the conceptualization of the COVID-19 transmission model which is used in this research.

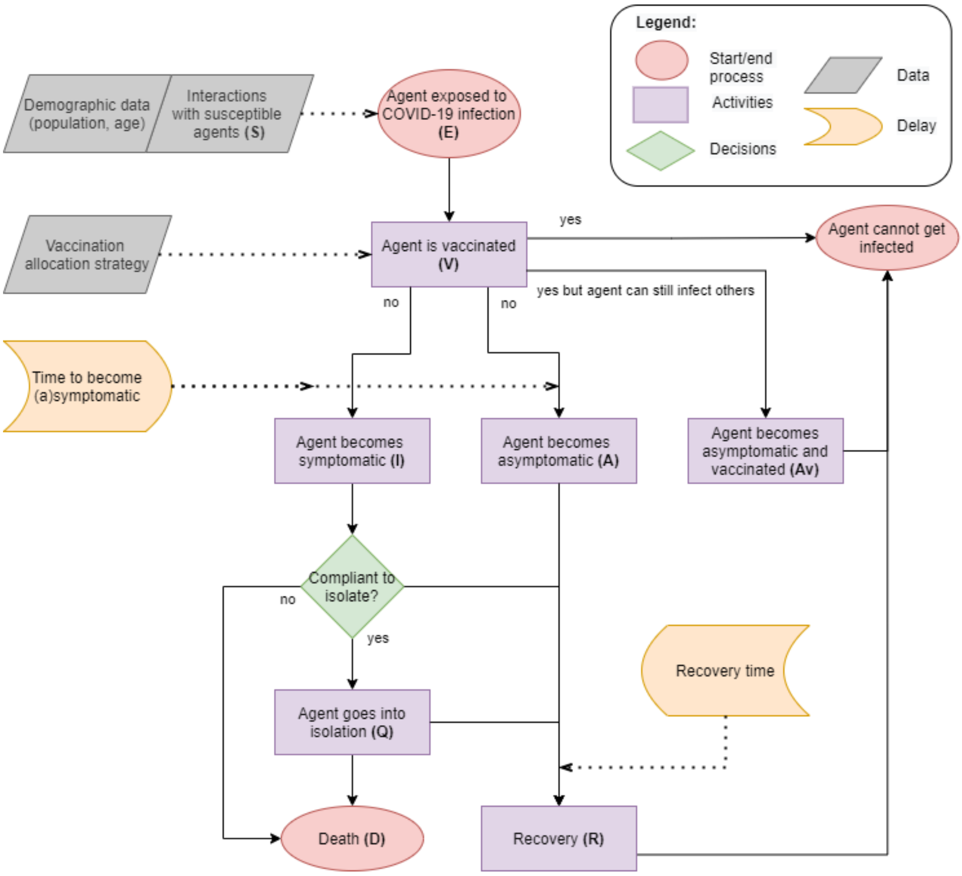


Figure D.4: Sub-concept of an epidemic model for COVID-19 transmissions

D.2 FORMALIZATION

D.2.1 Concept IV: Formalization of a COVID-19 transmission model

Equations for Flows of different Infection Stages

Equations as presented below are used to define different infection stages, to formalize the COVID-19 transmission model.

$$\frac{\Delta S_{ij}}{\Delta t} = R_{ij} - \varepsilon M - \frac{\beta_1 S_{ij}}{N} \tag{D.1}$$

$$\frac{\Delta E_{ij}}{\Delta t} = -\sigma E_{ij} + \frac{\beta_1 S_{ij}}{N} \tag{D.2}$$

$$\frac{\Delta V_{ij}}{\Delta t} = R_{ij} + \varepsilon M - \frac{\beta_2 S_{ij}}{N} \tag{D.3}$$

$$\frac{\Delta A_{ij}}{\Delta t} = (1-p)\sigma E_{ij} - \gamma A_{ij} \tag{D.4}$$

$$\frac{\Delta Av_{ij}}{\Delta t} = \sigma E_{ij} - \gamma Av_{ij} \tag{D.5}$$

$$\frac{\Delta I_{ij}}{\Delta t} = p\sigma E_{ij} - \alpha I_{ij} \tag{D.6}$$

$$\frac{\Delta Q_{ij}}{\Delta t} = \alpha I_{ij} - \omega Q_{ij} \tag{D.7}$$

$$\frac{\Delta R_{ij}}{\Delta t} = \gamma A_{ij} + (1-\delta)\omega Q_{ij} - R_{ij} \tag{D.8}$$

$$\frac{\Delta D_{ij}}{\Delta t} = \delta\gamma Q_{ij} \tag{D.9}$$

D.2.2 Age-based infection forces for Rohingyas and Bangladeshi

β_1 describes the force of infection. This parameter controls the rate of the spread (i.e. the probability of a transmission between susceptible and infectious individuals). In this research, different forces of infection are considered for different age-groups and sub-population, based on estimations of Davies et al. [2020]. As no specific data exists on the force of infections in Bangladesh, this research uses estimated data on age-based susceptibility from 6 countries [Davies et al., 2020]. This data is translated to a force of infection for the Bangladesh population. For Rohingyas, data from Hub [2021] indicates a weaker infection force compared to the host communities: the number of positive tests against the total number of tests is 9.1% against just 1.3% for Bangladeshi versus Rohingyas respectively, in the period March 2020-April 2021. Therefore, infection forces are estimated based on this difference.

Table D.1: Age-based force of infection of Bangladeshi with COVID-19 symptoms, based on estimations by Davies et al. [2020]

Age	β_1	**Combined age**	β_1 **(simplified)**
0-9	0.4	Children (<18)	0.39
10-19	0.38		
20-29	0.79	Young adults (20-40)	0.83
30-39	0.86		
40-49	0.8	Older adults (40-60)	0.81
50-59	0.82		
60-69	0.88	Elderly	0.81
>70	0.74		

D.2.3 Age-based symptomatic rates for Rohingyas and Bangladeshi

To determine the age-based rate of symptomatic individuals for the two sub-populations, data is used from a research by Mannan et al. [2021]. This data shows the number of absolute and reported asymptomatic and symptomatic individuals in Bangladesh, with a sample size of 1021 individuals. Based on these data, a ratio of symptomatic individuals (as shown in table D.3) is calculated as a ratio of symptomatic individuals per age-group against the total number of symptomatic and asymptomatic individuals per age group.

For Rohingyas, this symptomatic rate is different, as concluded by Lopez-Pena et al. [2020]. In general, Rohingyas show symptoms such as fever, dry coughs or fatigue by only 24% of known cases. Therefore, the estimated age-based symptomatic rate for Rohingyas is based on a proportion of 24%, using the data from the Bangladesh community.

Table D.2: Estimated Age-based force of infection of Rohingyas with COVID-19 symptoms

Age	β_1	Combined age	β_1 (simplified)
0-9	0.4	Children (<18)	0.05
10-19	0.38		
20-29	0.79	Young adults (20-40)	0.12
30-39	0.86		
40-49	0.8	Older adults (40-60)	0.11
50-59	0.82		
60-69	0.88	Elderly	0.11
>70	0.74		

Table D.3: Age-based rate of Bangladeshi with COVID-19 symptoms [Mannan et al., 2021]

Age	Symptomatic	Combined age	Symptomatic
0-9	0.56	Children (<18)	0.70
10-19	0.84		
20-29	0.87	Young adults (20-40)	0.88
30-39	0.89		
40-49	0.94	Older adults (40-60)	0.91
50-59	0.88		
>60	0.95	Elderly	0.95

Table D.4: Estimated age-based rate of Rohingyas with COVID-19 symptoms

Age	Symptomatic	Combined age	Symptomatic
0-9	0.14	Children (<18)	0.18
10-19	0.21		
20-29	0.21	Young adults (20-40)	0.22
30-39	0.22		
40-49	0.23	Older adults (40-60)	0.23
50-59	0.22		
>60	0.23	Elderly	0.23

D.2.4 Concept | Formalization of the open-system refugee camp

In table D.5 and D.6, data is shown which is used for modeling demographic compositions of both Rohingyas households and host community people.

Table D.5: Household composition Rohingyas [Bhatia et al., 2018; Rieger et al., 2020]

Household composition:	Rohingyas	Host communities
Median household size	6	5
Children (<18 years)	65%	50%
Young adults (20-40 years)	20%	25%
Older adults (40-60 years)	10%	20%
Elderly (>60 years)	5%	5%

Table D.6: Household composition Rohingyas in Nayapara RC & host communities households around Nayapara RC

	Rohingyas	Bangladeshi	Source
Population	22.677	40.032	Humanitarian Response
Households	4306	8006	Humanitarian Response
Shelters	781	-	HDX Data
Median household (hh) size	6	5	Lopez-Pena et al.
Children per hh <18 y	65%	50%	Lopez-Pena et al.
Young adults per hh 20-40 y	20%	25%	Lopez-Pena et al.
Older adults per hh 40-60 y	10%	20%	Lopez-Pena et al.
Elderly per hh >60 y	5%	5%	Lopez-Pena et al.

D.2.5 Formalization of integrated concept

Global model variables

Global variables range over global setup parameters, global variables and global reporters. Global setup parameters are initial settings for the model setup. Global variables are parameter values which can affect all agents. Global reporters comprise sums of global variables.

Global setup parameters:

- **Lockdown type.** String, [”no lockdown”, ”conditional lockdown”, ”unconditional lockdown”]. Determines the openness of the camp, allowing host communities to enter the camp.
- **Strictness of conditional lockdown.** Integer [0-10]. Determines the number of Bangladeshi who can enter the camp in case of a conditional lockdown.
- **Initial infection rate.** Integer, [0-100]. Determines the initially infected number of individuals from the beginning of a model run, determined separately for both Bangladeshi and Rohingyas.
- **The vaccine allocation strategy.** String, [e.g. ”Age-based strategy”]. Determines the vaccine allocation strategy which will be used to vaccinate individuals.
- **Available vaccines.** Integer, [0-100]. Determines the availability of vaccines for both populations.

Global variables:

- **Time**. The time represents the time of the day, triggering events in the model. Time differentiates between minutes, hours and days.
- **Initial number of Bangladeshi.** Integer [> 0]. Determines the number of Bangladeshi living in host community sites.
- **Initial number of Rohingyas.** Integer [> 0]. Determines the number of Rohingyas living in the refugee camp site.
- **Camp openness.** String [”open”, ”partially open”, ”closed”]. Determines whether (a number of) Bangladeshi can enter the camp sites.
- **Currently available vaccines (per group).** Integer, [0-*]. After starting the model, vaccines are allocated until no more available vaccines exist. Here, depending on a vaccine allocation strategy, vaccines are available for specific groups in each population.

Global reporters:

- **Count interactions.** Integer [>= 0]. The number of people visiting a certain activity destination.

- **Count Bangladeshi in camp.** Integer [>= 0]. The number of Bangladeshi who can enter the Rohingya camp.
- **Count Rohingyas/Bangladeshi on vicinity markets.** Integer [[>= 0]. The number of Rohingyas/Bangladeshi who have visited an in-camp or vicinity market.
- **Count Rohingya children at school.** Integer [[>= 0]. The number of Rohingya children who have visited school.

Agent & patch variables

Agent & object variables are agent and object-specific variables. Therefore, agent/object variables are parameter values which can affect only one specific agent or object. Agents and objects are classified through certain actions and their properties. The following agents are considered

Rohingya refugee shelters have:

- A location *myhome* (integer, *patch-here*)
- A household (list)
- A sick household (list)
- A vaccinated household (list)
- A household size (integer)
- A representative leaving the house (an agent)
  - A *walker* represents someone above 18 years leaving the house
  - A *child walker* represents a child who goes to school
- An activity schedule:
  - A time an activity (integer)
  - A spending time for an activity (integer)

Both Rohingya individuals and Bangladeshi have:

- A destination for an activity (string)
- Age-group (string)
- Occupancy when left the house (string)
- A preference for an in-camp market or vicinity market (string)
- A queue time in the line of one of the facilities (integer)
- A COVID-19 infection (boolean)
- A current COVID-19 infection stage (string)
- A next COVID-19 infection stage (string)
- A time duration for an infection stage (integer)
- Compliance to stay-at-home (boolean)
- A vaccination status (boolean)
- An age-based transmission force for COVID-19 (float)

Rohingya individuals have:

- An individual level of compliance (integer)

Host community/Bangladeshi have:

- Host is in camp? (boolean)

- Permission to enter the camp (boolean)

Patches have:

- A patch length (float)
- A queue distance (float)

In this research, Rohingyas are represented as households. Households are defined as a clusters of refugees, living together [Bhatia et al., 2018]. Refugee shelter households have:

- A household size
- A demographic household composition
- A location
- A number of individuals vaccinated
- A weekly activity schedule:
  - A day when they visit a market
  - A day when they visit food collecting points
- A daily activity schedule:
  - A time when they visit a mosque
  - A time when they visit a market
  - A time when they go to water & sanitation
  - A time when they go to a food-collection point
- An individual, leaving the shelter, who have:
  - An activity destination
  - A spending time at an destination
  - An age
    1. Age-specific disease transmission rates
  - A transmission-profile related to activity
  - A transmission-profile related to age
  - A health-risk profile related to activity
  - A health-risk profile related to age
  - A vaccine effectiveness rate
  - Compliance
  - With a health-status
  - With a know health-status
  - With a health-status time

D.3 FULL LIST OF MODEL ASSUMPTIONS & SIMPLIFICATIONS

An complete overview of the model assumptions and simplifications is listed below. A distinction for each sub-concept is made for structuring each assumption/simplification.

Assumptions & simplifications for agent interactions (sub-concept 1)

- Households range between 5 to 7 family members. In reality, household sizes have a wider range, but for simplicity the median is chosen with for50% of other households either 5 or 7 household members

- A shelter increases livelihood by executing daily activities and interacting with other people.
- Children visit markets as well.
- Household representatives visit markets once a week.
- An individual knows to be infected by COVID-19 if an symptomatic infection takes place.
- No individual from the host community can enter the camp/market without permission. Here, entry points of the camp are assumed to be guarded strictly and no other entry points exist in the camp.
- In-camp facility visiting represents visiting a mosque, water point, food point, sanitation facility or learning center
- Older people are assumed to execute daily interactions at the markets as well. Derived from insights from the interviews, this is an important source of gaining livelihood for elderly.
- Shelters define a daily activity schedule where only one of the household members execute these activities.
- Interactions are conceptualized as the visitation of some public location. Other interactions (e.g. meeting a neighbour around a refugee's shelter) is not considered.
- The moving of agents to a new destination is simplified by not including travel times. This is assumed for model simplicity: infections are assumed to be the result of spending time in a concentrated area with big numbers of other individuals around.
- No interactions take place during the nights.

Assumptions & simplifications for COVID-19 infection model (sub-concept 2)

- COVID-19 transmissions can happen from vaccinated people to susceptible people for vaccine efficacy which is lower than 100%.
- Re-infection can take place for recovered people after 2 months
- Asymptomatic infections never result in deaths, only symptomatic infections do.
- If infected as a vaccinated individual, it will always result in a asymptomatic infection.
- External infections (representing infections from outside the population of study) are simplified as the occurrence of a random-based infection of a certain household.
- COVID-19 infections happen by meeting other people inside 1.5 meter distance, and infection chances increase over time. Spending time with someone close over 15 minutes always results in an infection.
- Healthcare facilities are left out of scope

Assumptions & simplifications for vaccine allocation strategies (sub-concept 3)

- Willingness to get vaccinated by individuals is assumed to be 100%.
- Vaccines are assumed to have an effectiveness-rate of 100% or 90% for simplicity.
- The number of vaccines for an individual is assumed not an important factor.
- Available vaccines are all distributed or according to the chosen allocation strategy.

Assumptions & simplifications for restricting measures (sub-concept 4)

- The government is assumed to have full knowledge on the number of COVID-19 infections to calculate the reproduction number.

- For simplicity, the reproduction number is based on existing data only, no forecasting techniques.
- The government decides on restricting measures based on the basic reproduction number only.

D.4 FORMALIZED CONCEPTS FOR VACCINE ALLOCATION STRATEGIES

D.4.1 Concept of vaccine allocation mechanism for the 'children first' strategy

Figure D.5 presents the formalized concept of the vaccine allocation mechanism for the 'children first' strategy as it is used in this research.

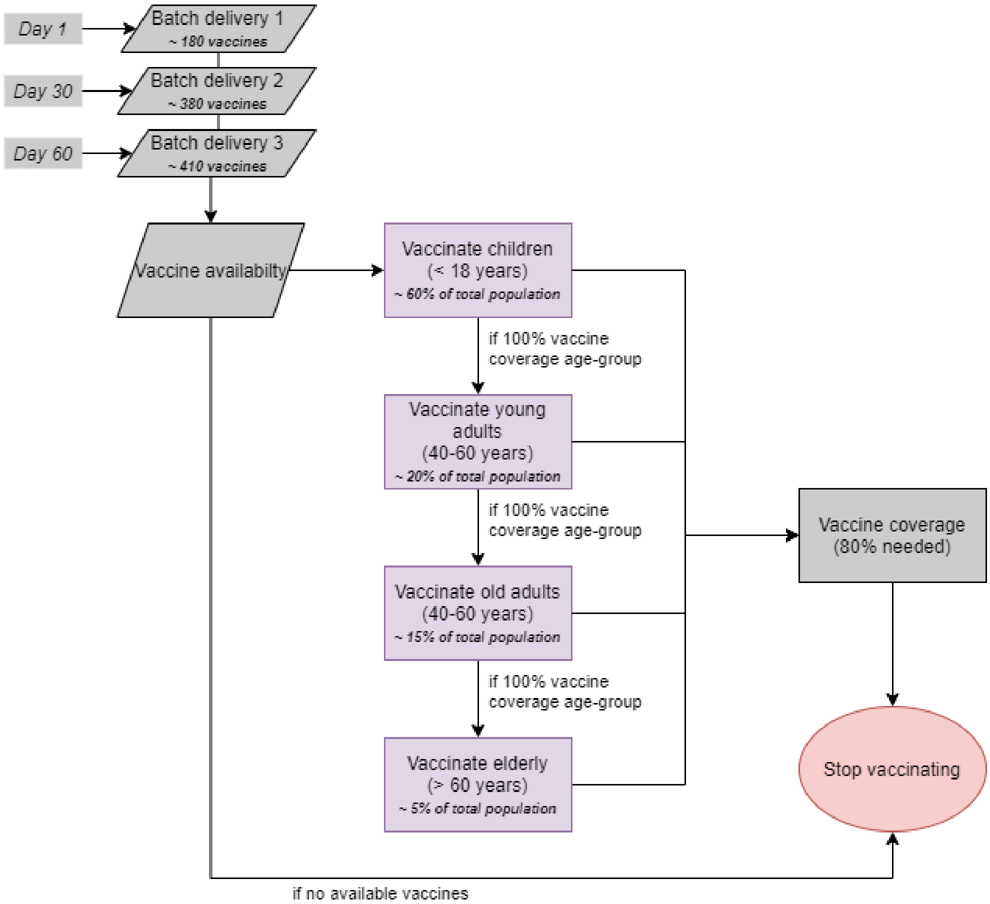


Figure D.5: A formalized concept for the vaccine allocation mechanism for the 'children first' strategy

D.4.2 Concept of vaccine allocation mechanism for the 'equalizing' strategy

Figure D.6 presents the formalized concept of the vaccine allocation mechanism for the 'equalizing' strategy as it is used in this research.

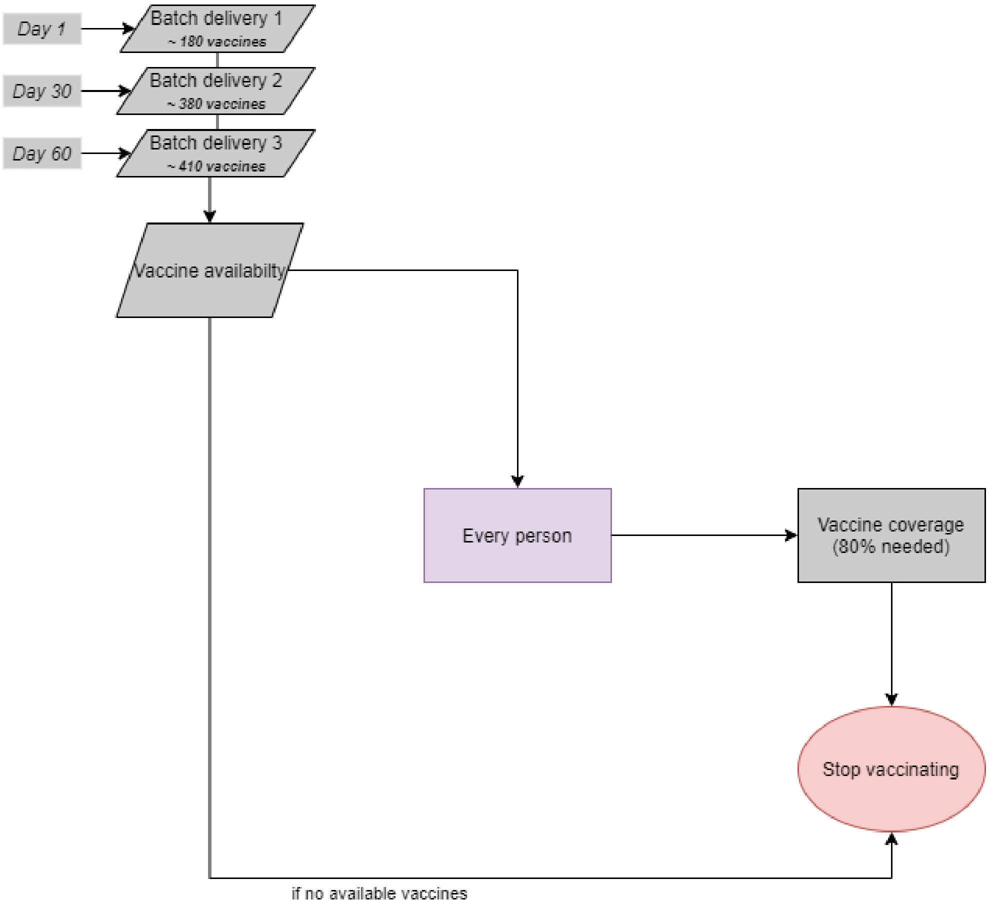


Figure D.6: A formalized concept for the vaccine allocation mechanism for the 'children first' strategy

D.4.3 Concept of vaccine allocation mechanism for the 'Bangladesh only' strategy

Figure D.7 presents the formalized concept of the vaccine allocation mechanism for the 'Bangladesh only' strategy as it is used in this research.

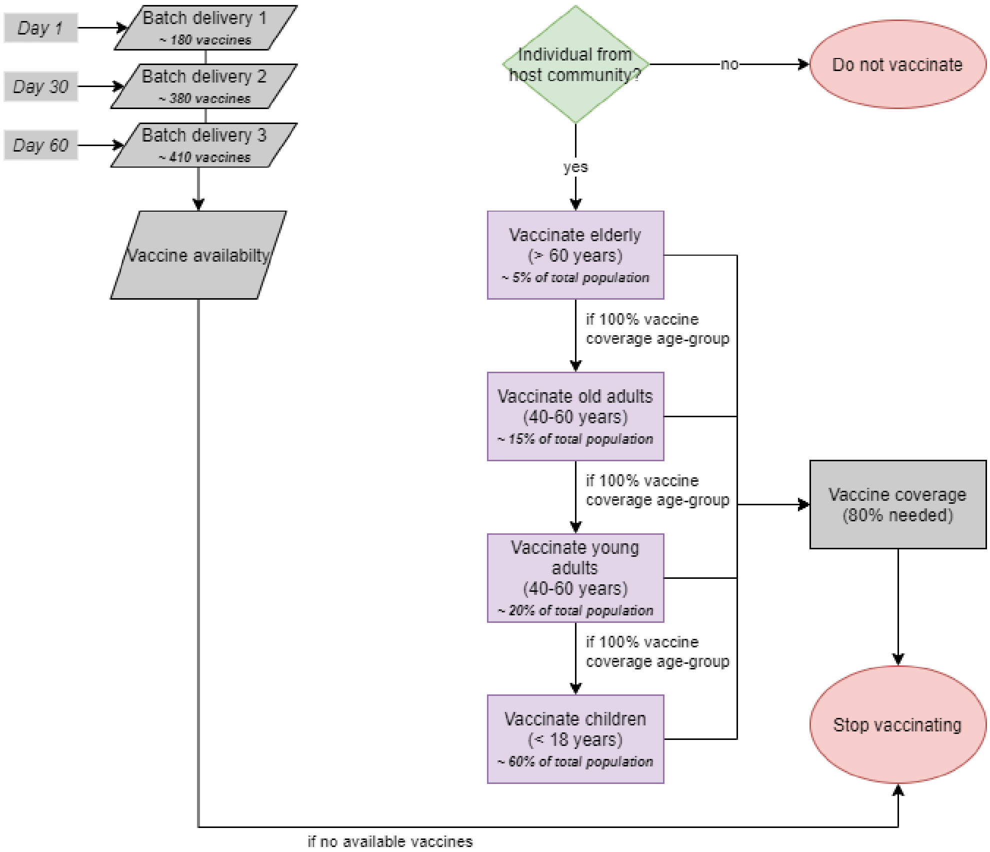


Figure D.7: A formalized concept for the vaccine allocation mechanism for the 'Bangladesh only' strategy

D.4.4 Concept of vaccine allocation mechanism for the 'Transmission group' strategy

Figure D.8 presents the formalized concept of the vaccine allocation mechanism for the 'Transmission group' strategy as it is used in this research.

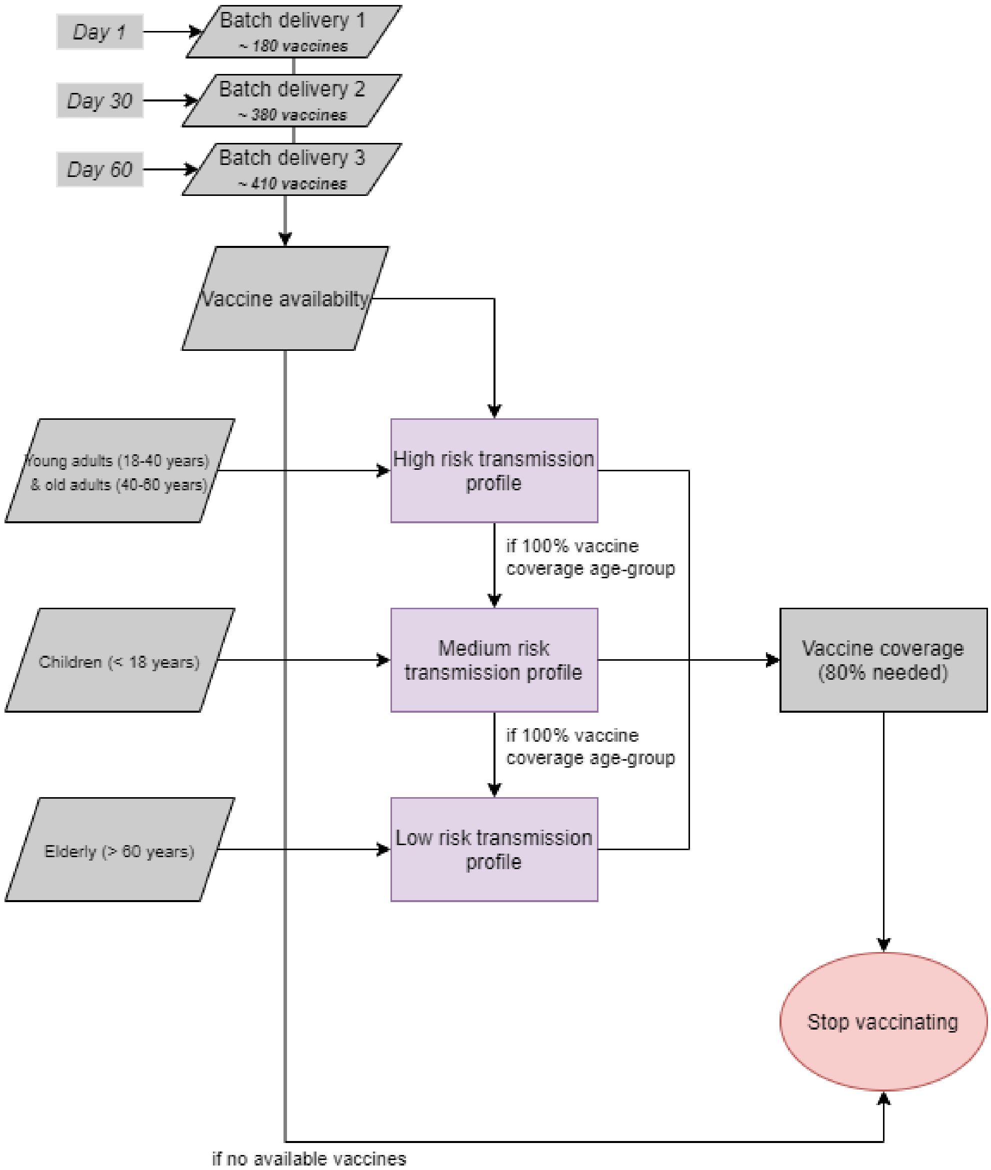


Figure D.8: A formalized concept for the vaccine allocation mechanism for the 'Transmission group' strategy

E MODEL FORMALISATION & IMPLEMENTATION

E.1 EXAMPLES OF MODEL NARRATIVE

In this appendix, an example is presented of the model narrive which has been used to create and formulate the model setup and parameter settings of the model.

E.1.1 Example 1: Model Set-up

At first, a visual camp environment is created in the ABM, representing the Nayapara Refugee Camp environment. Within this environment, the agents are created and their interactions happen inside this environment. As a first step, the physical environment is created. With data on the Nayapara RC and by studying different infrastructural maps of the camp environment, a number of shelters with according household compositions and population sizes, facilities and a host community is initialized. The following steps have been followed for this:

To set-up the model:

- Clear all variables. Now, all variables are cleared-up and ready for a new model run.
- Reset time to zero. A new day and model running time a created.
- Create a new day by setting the Day? false
- Set-up the camp environment:
  - Create a physical camp environment for both the Rohingya shelters, the hosting community and for activity locations. For this, three physical aspects are created:
    * Shelter places (space where Rohingya shelters are located)
    * Host community places (space where host communities live, outside the camp)
    * Roads (spaces where the interactive activities take place)
  - Create a number of interactive destinations based on data on these destinations (see table 4.3). The location of these destinations is based on a simplified representation of an infrastructural map of the Nayapara RC environment by Humanitarian Response [2017] and Rohingya Camp Map [2018]. The interactive destinations take place on roads.
- Set-up Rohingya shelters:
  - Create shelters in the shelter place area, based on the population data of the studied block (see table 4.4).
  - Give each shelter a size, shape, color & location.
  - Define the household composition of each shelter, by defining its size (i.e. the number of Rohingyas living here) and its composition (i.e. a list of its family members). These data were derived from data on household composition, which can be found in table D.5. In the end, a household composition should look like a list of household members (e.g. an ”elderly”, ”adult” and ”child”).
  - Define the activity schedule of each shelter (see table 4.1). This activity schedule represents the time of the day (represented as a *tick*) the household initiates to execute this activity.

  - Set a specific chance of going to one of the vicinity market or to the smaller, in-camp market. This is based on the mixing pattern matrix from table 4.2.

- Set-up the host community:
  - Create the host community people, represented by individuals on the on host community places, based on the population data and household composition data (see table 4.4).
  - Give each individual a size, shape, color & location.
  - Define the host community's age-category. This age-category gives an age to each individual based on data from table D.5. Children are not defined, as they do not go to school inside the camps and have no other specific reason to enter the camps.
  - Define the activity schedule of each host community individual (see table 4.1). This activity schedule entails the activities where host community people enter the Rohingya camps if they want to.
  - Set a specific chance of going to one of the vicinity market or to the smaller, in-camp market. This is based on the mixing pattern matrix from table 4.2.

- Set-up refugee camp entry point:
  - To create camp openness, an entry point is created for host communities to enter the camps.
  - This entry point is created on the border of the Rohingya camp sites and the host community site, which is based on studying the infrastructural map of the Nayapara RC environment by Humanitarian Response [2017].
  - To model camp openness, the entry point has three different property values for "entry point openness":
    * "open": host communities can enter the camp freely under this condition
    * "partially open": part of the host community can enter the camp freely under this condition
    * "closed": no one from the host community can enter the camp under this condition

E.2 EXAMPLE 2: INITIATING AN ACTIVITY

The Rohingya population is conceptualized and modeled as a composition of shelter households, as it lowers computational time. For each household, a list is created of its members with children, young adults, older adults and elderly. But to model the interactions outside these shelters, individuals must be created who execute the activity and interact with others. These individuals have been modeled as *walkers*, members of a certain household pointed out as the one executing a certain activity from a shelter's activity schedule. For example, a household can consist of a *"child", "adult" and "elderly"*. In the morning, at a scheduled time of the day (see table 4.1), adults go to markets. In case of the example, the adult is pointed out as the *walker* from this household, and leaves the house in case it is healthy (or not compliant when infected). For the household this member is now at school for the given amount of time, where it interacts with other people. At this time, this individual cannot be called for other activities, until the adult has been called to return home.

The same process yields for other activities, from the activity list defined by each shelter. To create this process inside the model, the example from above is modeled as follows:

To go to market

- Input for this process is a time-trigger, representing the moment adult go to the market (called *"market-time"*). For this, the clock is running (representing days, hours and minutes). At 9am, adults need go to the market and a *walker* is created:

- Calculate the number of Rohingyas inside the household
- If that number is larger than zero, *a-walker* is reported.
- To make *a-walker* represent all adults of this household, a new list is created of this household containing its adults-members only. For this, a filter is applied filtering out all *"adults"*. It is then calculated how many children are represent in each household, up to maximum of four adults.
- If there are adults in a certain household, each household shelter hatches this number of adults. This means, a shelter hatches new agents with an individual shape, color, age and destination. Its *destination* will be one of the market inside the camps or the vicinity market.
- Based on these characteristics, this adult goes a market. The household updates its number of individuals remaining at a shelter. As adults leave the shelter, only older individuals remain.

E.3 EXAMPLES OF MODEL VERIFICATION

E.3.1 Example 1: Recording and Tracking Agent Behaviour

Recording and tracking agent behaviour covers the verification of different types of behavior of agents inside the model, by measuring certain indicators [Van Dam et al., 2012]. During the construction of the model, several types of behavior were implemented and tracked for verification. Some important examples are:

Process: sending out someone out of a shelter to execute a daily activity, including the knowledge to have someone sick or vaccinated at home.

- **Expected behavior:** different types of behavior were modeled regarding this process: randomly sending out individuals were modeled (i.e. shelters not minding sending out a sick person), sending out individuals only if a healthy person is available, always sending out someone who is vaccinated, and keeping individuals at home who comply with stay-at-home rules in case of and infection.
- **Verification:** To verify this behavior, several checks were performed to track the behavior of shelters sending out individuals. For this, tests were carried out with shelters containing only sick/healthy/vaccinated people and shelters with mixes of these. For each, it was verified whether a shelter sent out the right person, based on the behavioral conditions that were set-up. For this, an indicators measuring the number of vaccinated/sick/healthy people out of shelters was used.

E.3.2 Example 2: Recording and Single Agent Testing

Single Agent Testing covers the verification of behavior for one single agent [Van Dam et al., 2012]. The example here shows how the disease progression for individuals has been verified:

Process: disease progression of individuals

- **Expected behavior:** individuals with age and population-specific characteristics have different progressions of COVID-19 infection stages. For example, children are less likely to infect others than elderly. Also, symptomatic infections in the Rohingya population were less likely than the Bangladesh population. Another factor which was expected was the duration of an infection, for different disease infection stages.
- **Verification:** To verify the progression of a COVID-19 infection, different checks have been performed. To verify the difference of disease progressions over different age-groups, two models of disease progression were analyzed over time in a

model with one child and one elderly respectively. The same was done for two models containing only one Rohingya and one Bangladeshi. Here, a verification check was carried out by studying the development of an infection over time for one agent.

F EXPERIMENTS

F.1 SETUP OF TIME FOR EXPERIMENTATION

Table F.1 gives an overview of the other time-setups which have been used for each simulation run:

Table F.1: Model time settings for 1 simulation run

Time parameter	Number of ticks	Real-world time
Minutes	*1*	*5 minutes*
Hours	*12*	*60 minutes*
Days	*288*	*1 day*
Total running time	***25.920***	***90 days***

F.2 EXPERIMENTING MODEL SETTINGS

F.2.1 Model settings for zero base case

Table F.2 presents the initial model settings for the zero base case experiment:

Table F.2: Base case model setup (200 runs)

Model parameter	Parameter value
Lockdown-type	No lockdown
Dynamic camp regulation	No
Capacity vicinity market	Unlimited
Sending behavior	Random
Initial number of infections Rohingyas	1 infection
Initial number of infections Bangladeshi	1 infection
Wearing mask effectiveness	Moderate
Compliance included?	No
Rohingya population (shelters)	148
Host community population (people)	275
Visiting of markets	once a day
Visiting of shops	once a day
Visiting of in-camp facilities	multiple times a day
Number of vaccines	No vaccines

F.2.2 Model settings for single effects

Table F.3 presents the initial model settings for the experiments testing the single effect of different types of limited camp openness. Table F.4 presents the initial model settings for the experiments testing the single effect of different types of camp openness. Table F.5 presents the initial model settings for the experiments testing the single effect of different types of vaccine allocation strategies. Table F.6 presents the initial model settings for the experiments which combines camp openness with vaccine allocation strategies.

Table F.3: Experimental design for analysing single effects of base case model parameters (600 runs)

Single Effect Experiment	Two/three-level parameter value:	Explanation
1) Camp openness	no lockdown conditional lockdown unconditional lockdown	Testing different types of camp openness
2) Camp openness strictness	not strict R0 medium strict R0 very strict R0	Testing different types of stricness for camp openness
3) Camp & vicinity market capacity	10% allowance (very strict) 40% allowance (strict) 70% allowance (medium strict) 90% allowance (not strict)	Testing different capacities of camp and vicinity market entrances
4) 'Leaving shelter' behavior	"sending out random" "sending out healthy or vaccinated"	Testing different types of behavior related to leaving the shelter by individuals
5) Stay-at-home & wearing mask compliance	no compliance at all mask compliance stay-at-home-compliance both	Testing different types of behavior related to stay-at-home and mask-wearing compliance

Table F.4: Experimental design for camp openness regulation (200 runs per measure)

Camp Openness	Explanation	Variable openness
No lockdown	No camp openness restrictions	Camp capacity 100% Age capacity 100% Location capacity 100% Dynamic? yes/no
Unconditional lockdown	No camp openness, markets closed	Camp capacity 100% Age capacity 100% Location capacity markets 0% Capacity in-camp fac. 100% Dynamic yes/no
Conditional lockdown	Capacity-based closing of facilities	Camp capacity 30-70% Age capacity 100% Location capacity 30-70% Dynamic? yes/no
Subtype conditional lockdown	Closing markets	Camp capacity 0% Age capacity 100% Market capacity 0% Dynamic? yes/no
Subtype conditional lockdown	Closing for host community	Camp capacity 0% Age capacity 100% Market capacity 100% Dynamic? yes/no
Subtype conditional lockdown	Keeping elderly home	Camp capacity 0% Age capacity 0% elderly Market capacity 0% Dynamic? yes/no

F.3 SETUP OF SENSITIVITY ANALYSIS

Table F.7 presents the variations in parameter settings for the sensitivity analysis.

Table F.5: Experimental design for vaccine allocation strategies (300 runs per strategy)

Allocation strategy	Explanation	Variable vaccine availability
Age-based strategy, Elderly first	Vaccines are distributed up to capacity, prioritizing the older people first	3 batches, 10%/15%/.../70% available, 90/100% efficacy, incl/excl vacc. infectiousness
Age-based strategy, Children first	Vaccines are distributed up to capacity, prioritizing the children first	3 batches, 10%/15%/.../70% available, 90/100% efficacy, incl/excl vacc. infectiousness
Equalizing strategy	Vaccines are randomly distributed	3 batches, 10%/15%/.../70% available, 90/100% efficacy, incl/excl vacc. infectiousness
Elderly first, only Bangladeshi	Vaccines are allocated over the Bangladesh population only, elderly first	3 batches, 10%/15%/.../70% available, 90/100% efficacy, incl/excl vacc. infectiousness
Transmission group: Young & Old ad. only	Vaccines are distributed over the most frequent inhabitants of the camp first: young and older adults	3 batches, 10%/15%/.../70% available, 90/100% efficacy, incl/excl vacc. infectiousness

Table F.6: Combining restricting variables for interactions and infections with benefiting vaccine allocation strategies (200 runs per measure)

Measure	Variable min.	Variable max
Dynamic camp openness?	Low strictness	High strictness
Capacity strictness	Low capacity	High capacity
Leaving shelter behavior	"Send out random"	"Send out healthy or vaccinated if possible"
Compliance	No compliance	Both mask & stay-at-home compliance
Vaccine availability	Low availability	High availability

Table F.7: Sensitivity Analysis Experiment Setup (1000 runs)

Parameter for sensitivity analysis	Min. value	Max value	Value range
time of being infected by COVID-19	3 days	9 days	+/-50%
mask-protection-rate	0.25	0.75	+/- 50%
force of transmission	age & population dependent	age & population dependent	+/-50%
symptomatic-rate	age & population dependent	age & population dependent	+/-50%
Re-infectious time	age & population dependent	age & population dependent	+/- 50%

F.4 HYPOTHESES & EXPLANATION

With the use of type 1 hypotheses, different model parameter boundaries are defined, which serve as scenario values. To setup realistic scenarios, the context of the Rohingya refugee camps is studied and translated to match the parameters in the model (which has been discussed in chapter 5). Below, an overview is presented of these hypotheses and an explanation of each.

The following type 1 hypotheses have been tested regarding refugee behavior:

- **Type 1 Hypothesis 1:** *Higher dedication of household shelters to only send out a vaccinated or healthy person out of their shelter lowers the chance of infections happening outside shelters.* Here, it is expected if shelters are more commited to send out healthy or vaccinated household members, a lower chance of bringing back a COVID-19 infection after leaving a shelter is created.

- **Type 1 Hypothesis 2:** *Higher levels of complying to stay-at-home when being sick prevent others from being infected by sick individuals is expected to have a negative effect on the number of infections happening inside and outside refugee shelters.*

The following type 1 hypotheses have been tested regarding limited camp openness:

- **Type 1 Hypothesis 3: Initial Hypothesis for this experiment:** *(Partially) closing the camp and its facilities for people reduces infections.* Here, it is tested what effect different levels of (un)conditional lockdowns have on the number of infections and interactions which happen in the open camp environment. Here, it is expected an (un)conditional lockdown will reduce the number of infections inside the camp, as host communities are prohibited from entering the camp.
- **Type 1 Hypothesis 4:** *Low capacity of shared locations reduces interactions, causing less COVID-19 infections.* Here, is is tested what effect different levels of capacity-based interactions have on the number of infections. It is expected if the capacity of different activities (the camp and the vicinity market) is low, infections are less likely to grow.
- **Type 1 Hypothesis 5:** *A high level of strictness for the basic reproduction number $R0$ causes less interactions between refugees and host communities and therefore lowers the chance of infections.* Here, it is tested what effect different levels of governmental strictness is for dynamic camp openness. Here, different reproduction number thresholds are used to create different levels of outcomes. Here, it is expected that a higher strictness of governmental appearances has a balancing effect on the number of infections inside the camp if the camp is closed faster (with higher strictness), with the camp opening for longer after as infections reduce.

The following type 1 hypotheses have been tested regarding the comparing of vaccine allocation strategies:

- **Type 1 Hypothesis 6:** *The prioritization of age-based sub-groups for COVID-19 vaccines is most effective for sub-groups with a high chance of interacting with other individuals.* Here, it is assumed age-based sub-groups who have a higher chance of leaving their shelter also get more in contact with others and therefore have a higher share of being infected. In the Rohingya camp environment, these sub-groups are mainly young and older adults (18-60 years).
- **Type 2 Hypothesis 7:** *The prioritization of both sub-populations (both Rohingyas and host community Bangladeshi) is most beneficial for reducing the number of infections, as both sub-populations interact.* Here, it is expected both sub-groups meeting contribute to the infections, and therefore leaving out one of these groups would be undesirable.

The following type 1 hypotheses have been tested regarding the scarcity of vaccines:

- **Type 1 Hypothesis 8:** *When distributing vaccines up to 70% of the total population, no more infections occur and the camp can reopen its borders unconditionally.* Here, it is expeced if group immunity (based on recovered and vaccinated individuals) reaches 70%, the reproduction number does not exceed above 1 anymore (i.e. the spread of COVID-19 will drop to zero).
- **Type 1 Hypothesis 9:** *The delivering of COVID-19 vaccines over three batches which result in 80% coverage for the total population contributes to stop the spread of COVID-19 within that time.* Here, this hypothesis is based on the same argumentation as for type 1 hypothesis 8. Furthermore, it sketches the real-world expectations of delivering COVID-19 vaccines to both the Rohingyas and Bangladeshi over three batches over time.

G | MODEL DATA & RESULTS

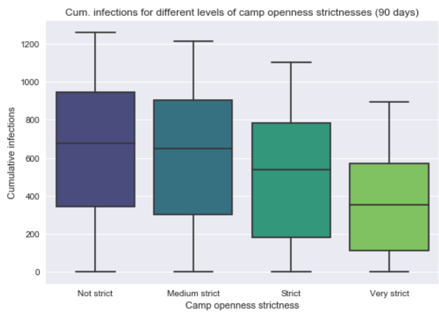
G.1 SINGLE EFFECT OF CAMP OPENNESS RESTRICTIONS: RESEARCHING CORRELATION

In this section, model results are presented for the five vaccine allocation strategies which are analysed in isolation. These results are discussed in section 7.4.

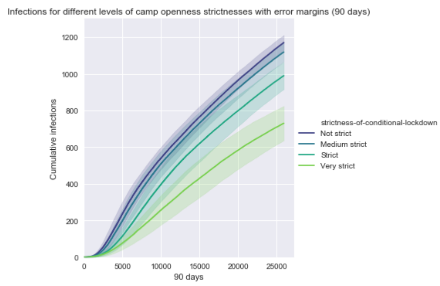
G.1.1 Effect of varying camp & market capacity

Initial Hypothesis for this experiment: *Lowering the capacity of shared locations reduces interactions, causing less infections.*

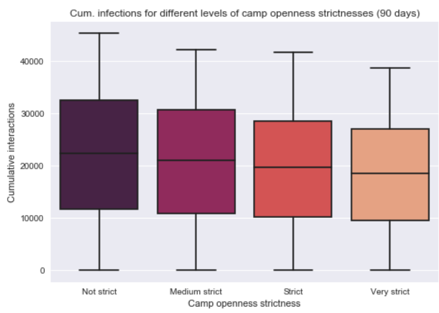
An effect measured is the variation of different capacities for host communities to enter the camp and for both populations to enter the vicinity market. Here, four types of camp/vicinity market capacity strictness are considered: *not strict*, *medium strict*, *strict* and *very strict*, respectively leaving room for *70*, *50*, *30* and *10*% of the interactions compared to a fully open camp. For this experiment, results are shown in figure G.1.



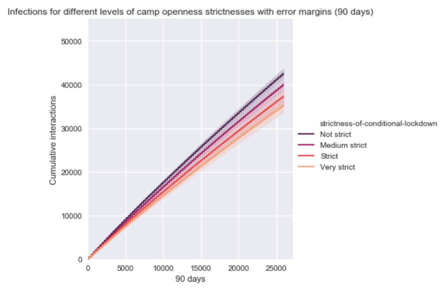
(a) Outcomes: number of infections



(b) Pattern: number of infections



(c) Outcomes: number of interactions



(d) Pattern: number of interactions

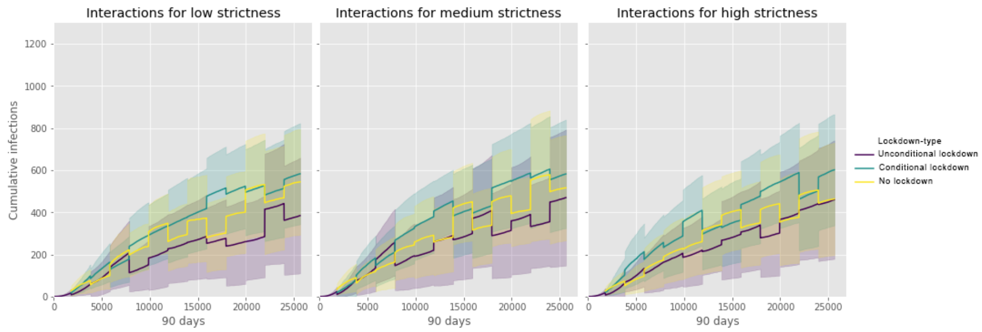
Figure G.1: Number of infections for different levels of camp entrance capacity: (a) number of infections, (b) number of infections, (c) outcomes: of number of interactions & (d) pattern: number of interactions.

Just as for the effect of dynamic camp openness, the effect of partially opening the camp is mainly reflected by the total number of infected people after 90 days, the speed in which COVID-19 spreads in the initial phase of the model. Namely, for different levels of camp/vicinity market capacities, the total number of infections drop by 17-55% compared to the base model. Also, the trajectory of the number of infections becomes more spread over time as the level of camp/vicinity market capacity increases. Just as for an unconditional lockdown, leaving room for only 10% of the number of people to enter the camp or visit the vicinity market, leads to a significantly slower spread in the first 30 days.

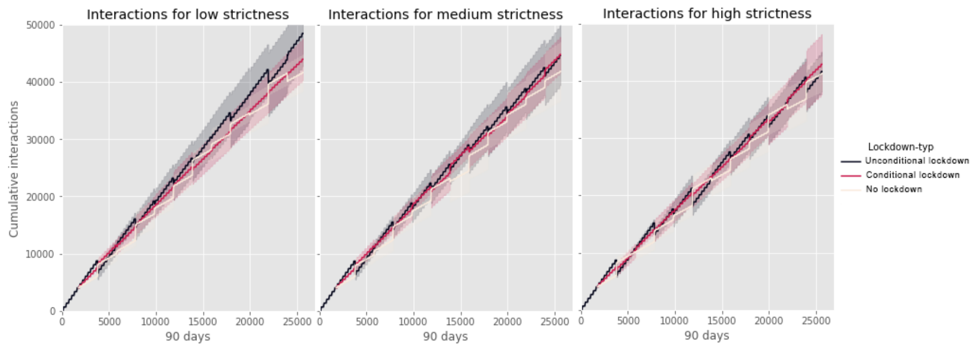
The latter statement is highlighted when reviewing the limiting the number of interactions which follow from this experiments. When studying the outcomes of the four boxplots in figure G.1a and G.1c, one can see the effect of reducing the number of interactions in a linear manner is a non-linear decline for the number of infections in line with these interaction reductions.

G.1.2 Dynamic Effect of Camp Openness

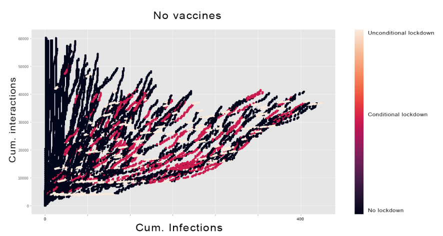
Figure G.2 shows the effect of implying different levels of lockdowns based on the weekly evaluation of $R0$, for different levels of strictness. Figure G.2c & G.2d show the effect of dynamic opening/closing the markets and camp environment for visitors. It shows how the implementation of vaccines has a significant reduction on infections, which therefore allows the camp to be open more often, with more interactions as a result.



(a) Total Infections



(b) Total interactions



(c) base case (no vaccines)

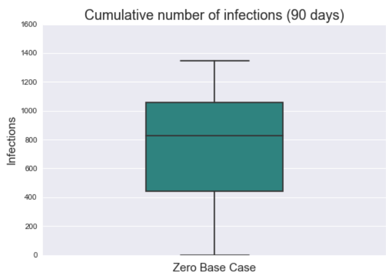
(d) Elderly first strategy

Figure G.2: Number of interactions for dynamic camp openness, based on reproduction number $R0$ for the: (a) number of infections & (b) number of interactions

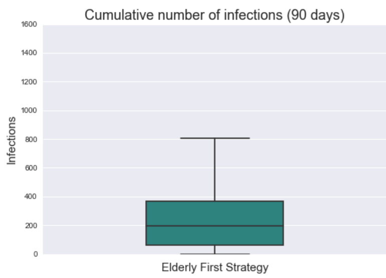
G.2 SINGLE EFFECTS OF VACCINE ALLOCATION STRATEGIES

In this section, model results are presented for the five vaccine allocation strategies which are analysed in isolation. These results are discussed in section 7.4.

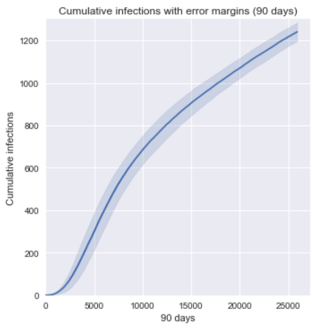
G.2.1 Elderly first Allocation Strategy



(a) Cum. infections (base case)

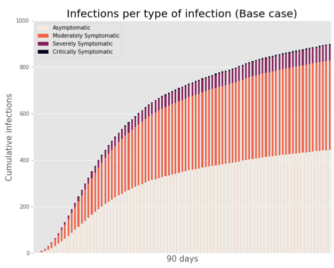


(b) Cum. infections

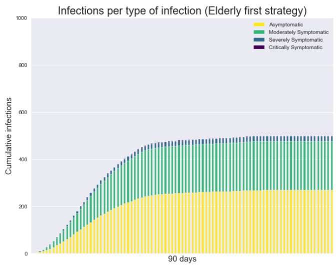


(c) Cum. infections (base case)

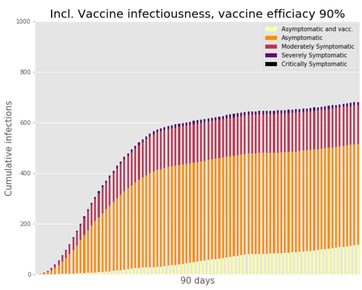
(d) Incl. vacc. infectiousness



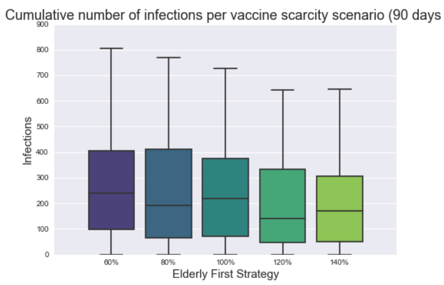
(e) Type of infection (base case)



(f) Excl. vacc. infectiousness



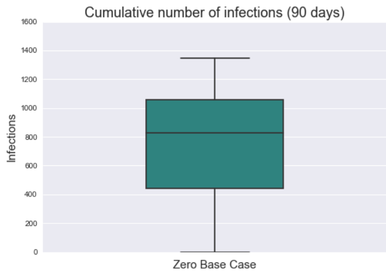
(g) Incl. vacc. infectiousness



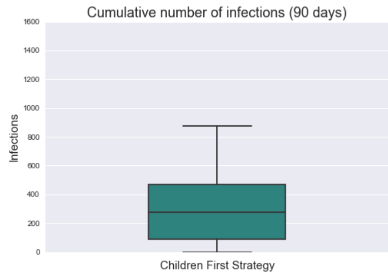
(h) Sensitivity to vaccine scarcity

Figure G.3: Model results for comparing base case model with the Elderly first vaccine allocation strategy

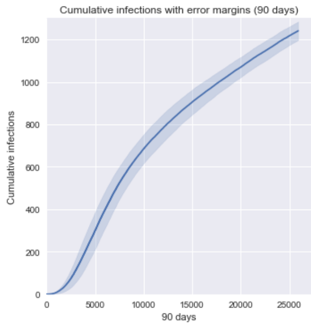
G.2.2 Children first allocation Allocation Strategy



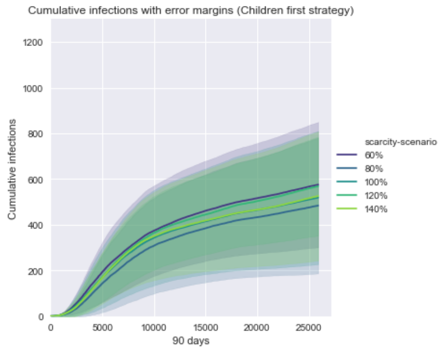
(a) Cum. infections (base case)



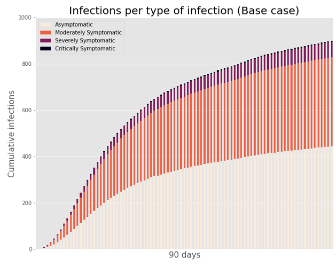
(b) Cum. infections



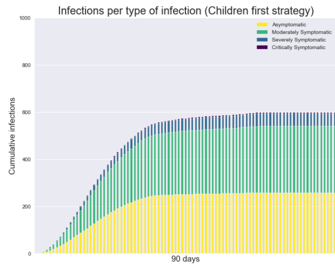
(c) Cum. infections (base case)



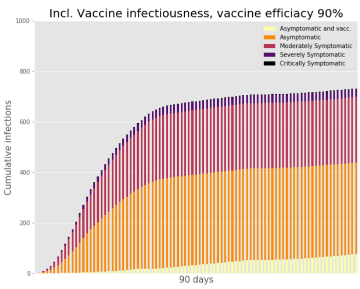
(d) Cum. infections



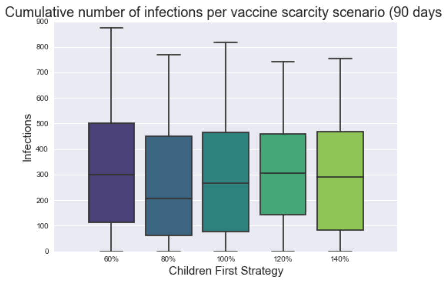
(e) Type of infection (base case)



(f) Excl. vacc. infectiousness



(g) Incl. vacc. infectiousness

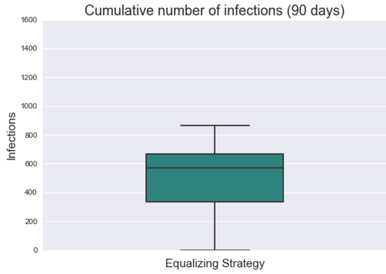


(h) Sensitivity to vaccine scarcity

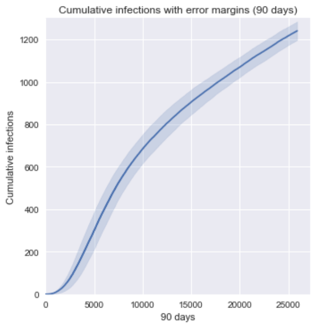
Figure G.4: Model results for comparing base case model with the Children first vaccine allocation strategy

G.2.3 Equalizing Allocation Strategy

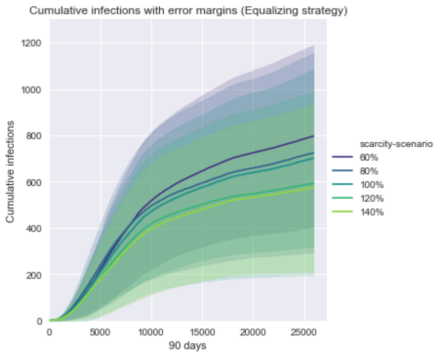
(a) Cum. infections (base case)



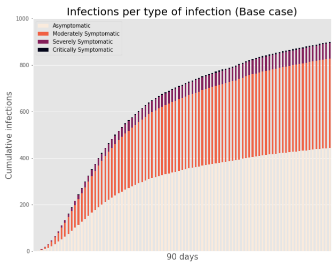
(b) Cum. infections



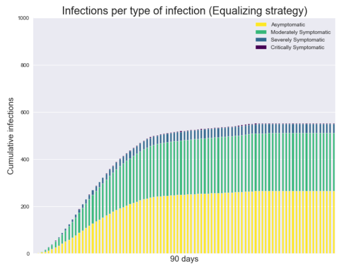
(c) Cum. infections (base case)



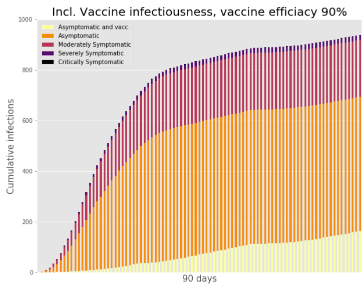
(d) Cum. infections



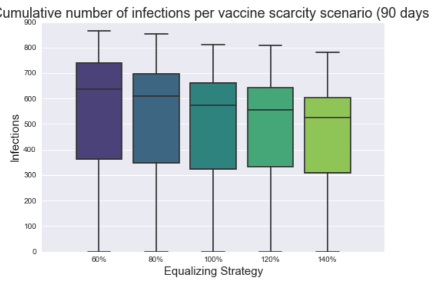
(e) Type of infection (base case)



(f) Excl. vacc. infectiousness



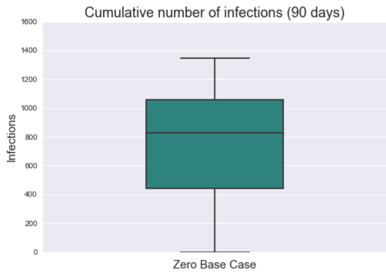
(g) Incl. vacc. infectiousness



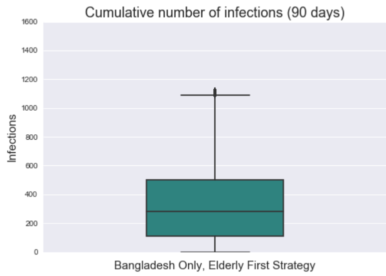
(h) Sensitivity to vaccine scarcity

Figure G.5: Model results for comparing base case model with the Equalizing vaccine allocation strategy

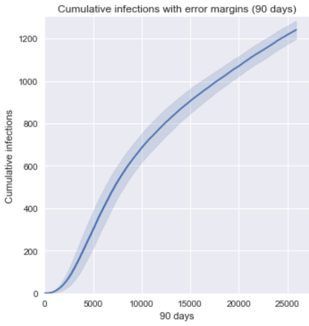
G.2.4 Bangladesh only Allocation Strategy



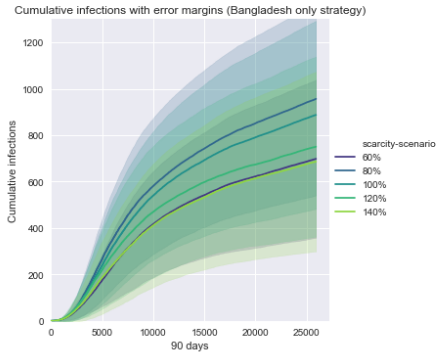
(a) Cum. infections (base case)



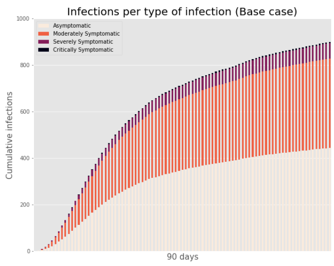
(b) Cum. infections



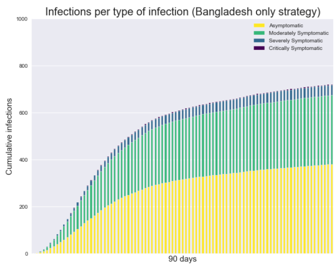
(c) Cum. infections (base case)



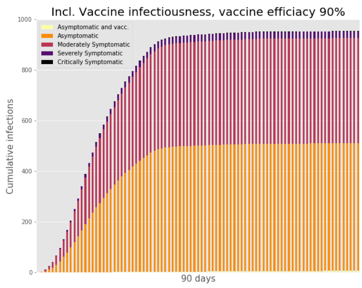
(d) Cum. infections



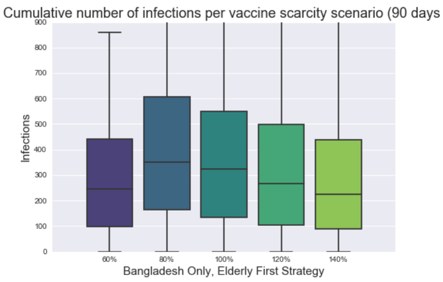
(e) Type of infection (base case)



(f) Excl. vacc. infectiousness



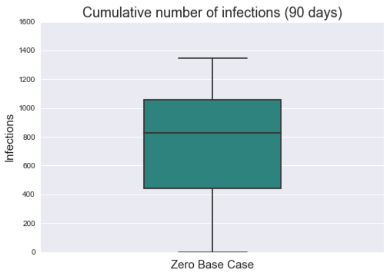
(g) Incl. vacc. infectiousness



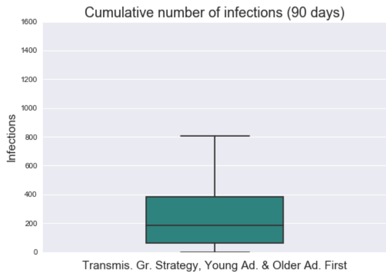
(h) Sensitivity to vaccine scarcity

Figure G.6: Model results for comparing base case model with the Bangladesh only vaccine allocation strategy

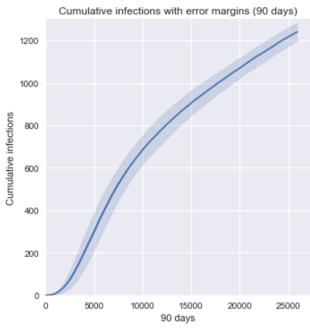
G.2.5 'Transmission group only' Allocation Strategy



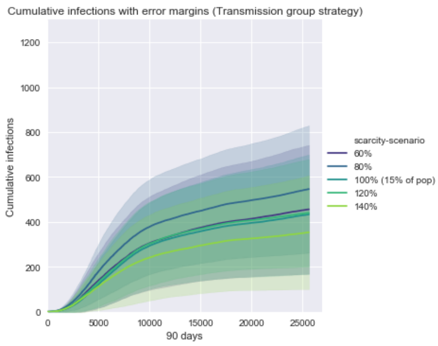
(a) Cum. infections (base case)



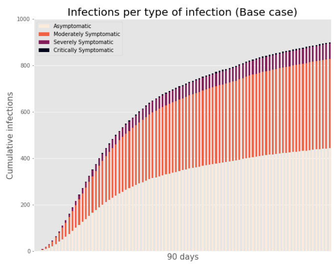
(b) Cum. infections



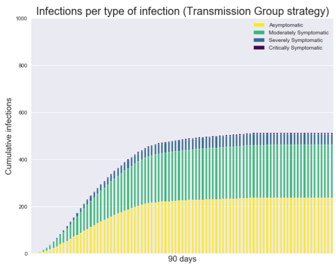
(c) Cum. infections (base case)



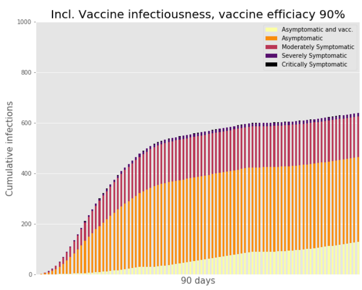
(d) Cum. infections



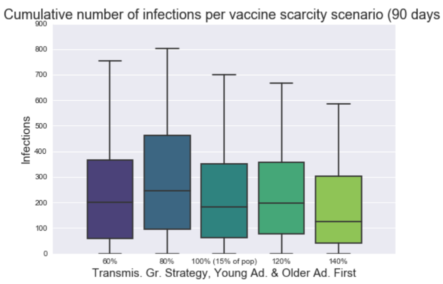
(e) Type of infection (base case)



(f) Excl. vacc. infectiousness



(g) Incl. vacc. infectiousness



(h) Sensitivity to vaccine scarcity

Figure G.7: Model results for comparing base case model with the Transmission group vaccine allocation strategy

G.2.6 Sensitivity to vaccine efficacy

Figure G.8 shows the sensitivity of infections for different levels of vaccine efficacy. Based on this analysis, an non-linear negative correlation between efficacy and infections is concludes.

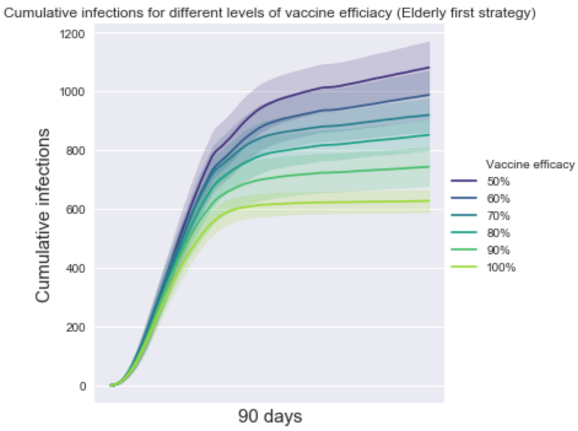
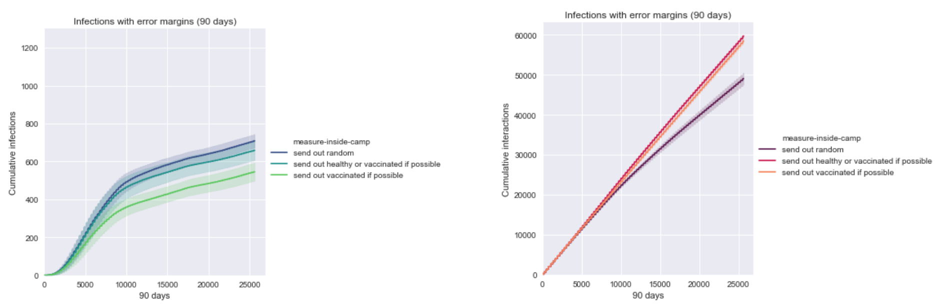


Figure G.8: Sensitivity of vaccine efficacy

G.3 MODEL RESULTS FOR TRADE-OFFS: DYNAMICS BETWEEN CAMP OPENNESS & VACCINE ALLOCATION STRATEGIES

G.3.1 Effect of "Leaving shelter behavior" rules

An effect measured is the introduction of 'leaving shelter behavior' rules. Here, household members decide whom to send out of their shelters, based on their health condition and the rule related to this. Two types of behavior are studied: *sending out random individuals* (i.e.no rules) or *sending out healthy or vaccinated people if possible*. For the second type of behavior, it is assumed individuals with symptoms *always know* to be infected and a *fraction of 10%* of individuals who remain asymptomatic knows (of which this fraction represents being tested with a positive outcome). The results for this experiment are shown in figure G.9.



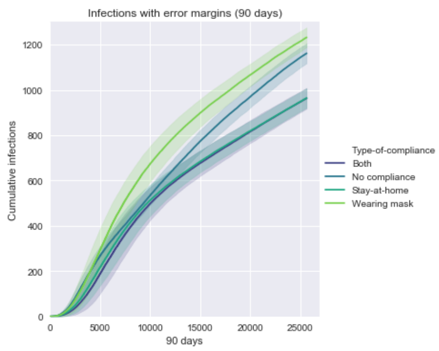
(a) (b)

Figure G.9: Number of infections & interactions for sending random individuals vs. healthy if available: (a) line plot of number of infections & (b) line plot of number of infections.

G.3.2 Effect of Compliance to Behavioral Rules

Initial Hypothesis for this experiment: *Higher levels of complying to stay-at-home when being sick or wearing a mask to prevent others from being infected by sick individuals is expected* *to have a negative effect on the number of infections happening.*

An effect measured is individual's compliance to staying home and/or wearing a mask in public, to reduce the risk of others getting infected by sick people. Compliance is determined in the same manner as for 'leaving shelter behavior': symptomatic and a fraction of asymptomatic individuals know to be sick, and therefore can be compliant or not. To measure its single effect, both types of compliance are measured separately. Also, the effects of not including and both including stay-at-home & wearing mask compliance are measured. Results are shown in figure G.10.

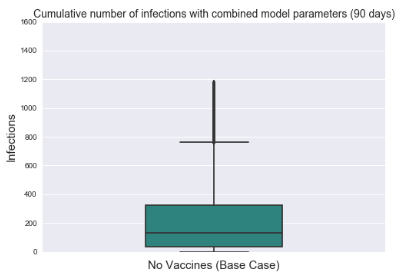


(a)

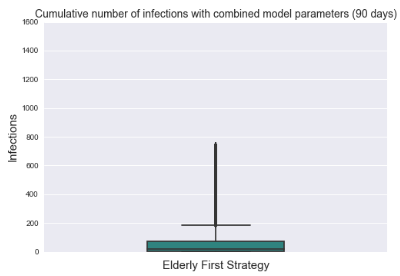
(b)

Figure G.10: Single effect of different types of compliance on: (a) infections & (b) interactions.

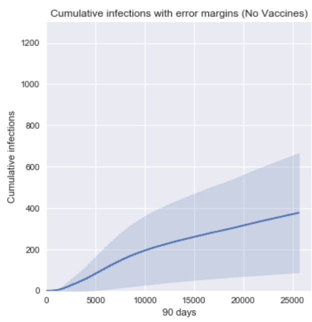
G.3.3 'Elderly first' allocation Allocation Strategy



(a) Outcomes: Cum. infections (base case)



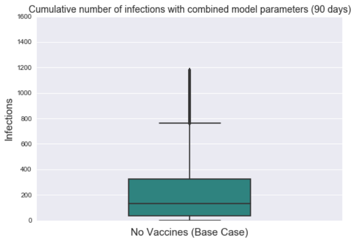
(b) Outcomes: Cum. infections

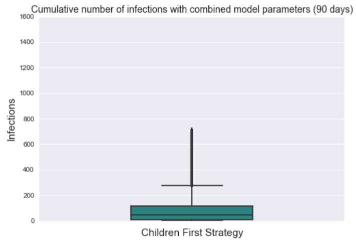


(c) Pattern: Cum. infections

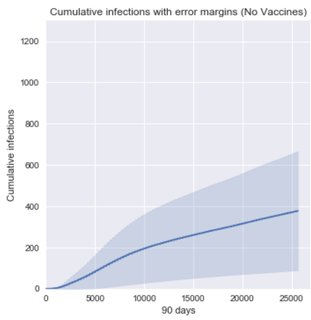
(d) Pattern: Cum. infections

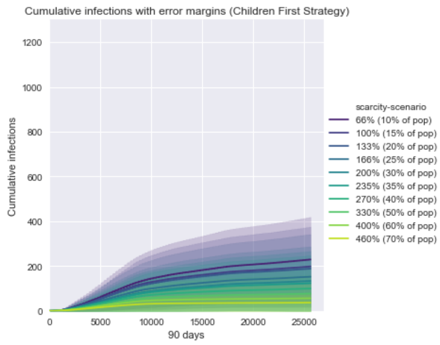
Figure G.11: COVID-19 infections: Boxplots for comparing the KPI's for the (a & c) base case & (b & d) the 'Elderly first' allocation Allocation Strategy.





(a) Outcomes: Cum. infections (base case) **(b)** Outcomes: Cum. infections



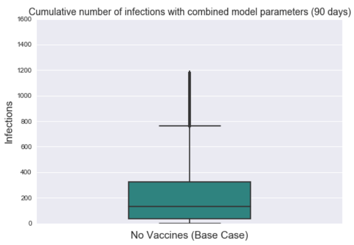


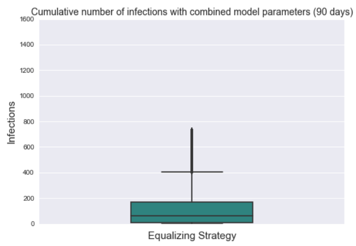
(c) Pattern: Cum. infections **(d)** Pattern: Cum. infections

Figure G.12: COVID-19 infections: Boxplots for comparing the KPI's for the (a & c) base case & (b & d) the 'Children first' allocation Allocation Strategy.

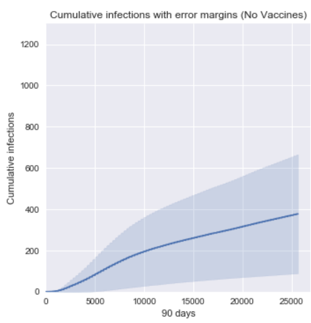
G.3.4 'Children first' allocation Allocation Strategy

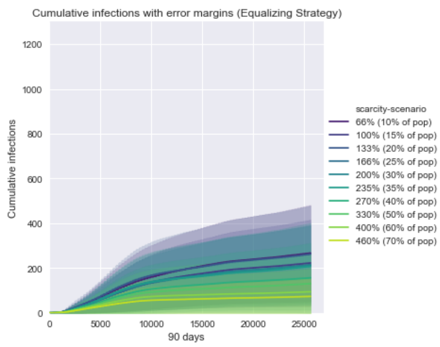
G.3.5 'Equalizing' Allocation Strategy





(a) Outcomes: Cum. infections (base case) **(b)** Outcomes: Cum. infections

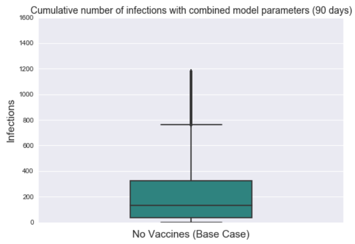




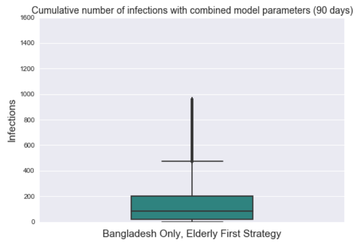
(c) Pattern: Cum. infections **(d)** Pattern: Cum. infections

Figure G.13: COVID-19 infections: Boxplots for comparing the KPI's for the (a & c) base case & (b & d) the 'Equalizing' Allocation Strategy.

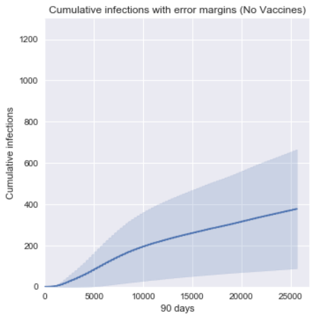
G.3.6 Bangladesh only Allocation Strategy



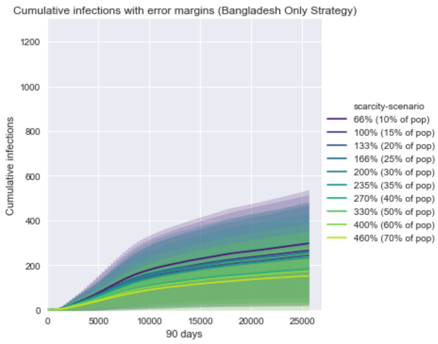
(a) Outcomes: Cum. infections (base case)



(b) Outcomes: Cum. infections



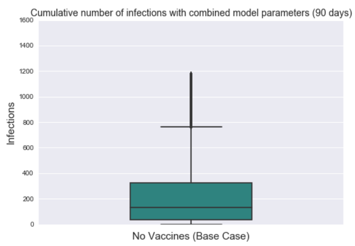
(c) Pattern: Cum. infections



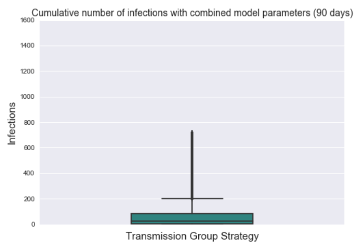
(d) Pattern: Cum. infections

Figure G.14: COVID-19 infections: Boxplots for comparing the KPI's for the (a & c) base case & (b & d) the 'Equalizing' Allocation Strategy.

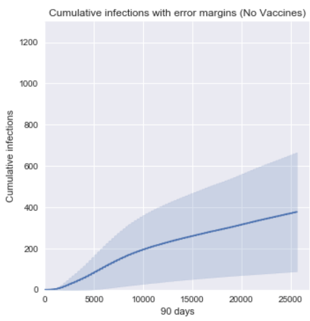
G.3.7 'Transmission group only' Allocation Strategy



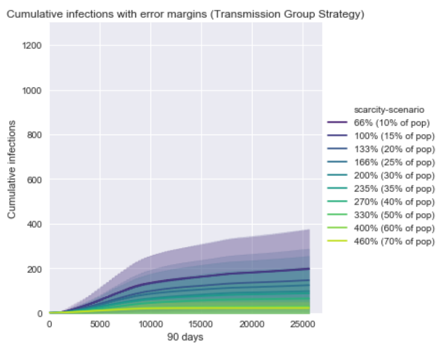
(a) Outcomes: Cum. infections (base case)



(b) Outcomes: Cum. infections



(c) Pattern: Cum. infections

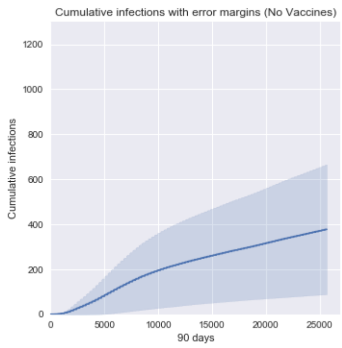


(d) Pattern: Cum. infections

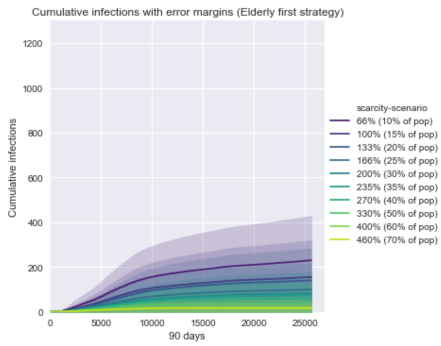
Figure G.15: COVID-19 infections: Boxplots for comparing the KPI's for the (a & c) base case & (b & d) the 'Transmission group only' Allocation Strategy.

G.4 ANALYSIS ON DYNAMICS BETWEEN CAMP OPENNESS & VACCINE ALLOCATION STRATEGIES

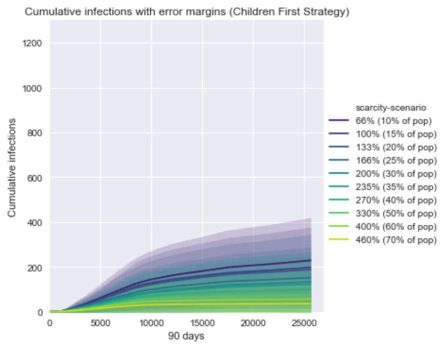
Figure G.16 shows the cumulative number of infections for combined parameter testing.



(a) base case (no vaccines)

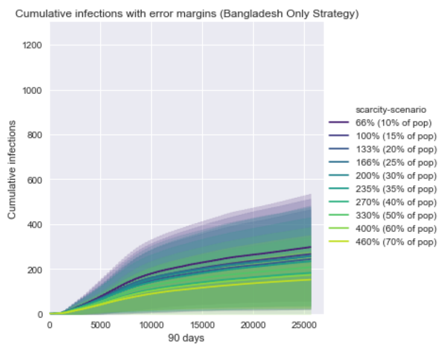


(b) Elderly first strategy

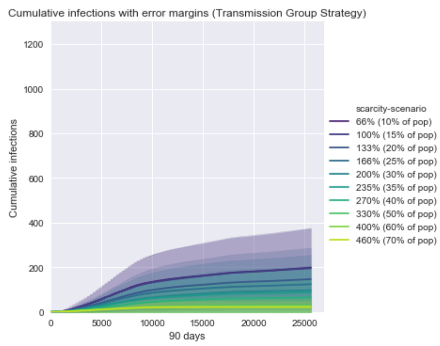


(c) Children first strategy

(d) Equalizing strategy



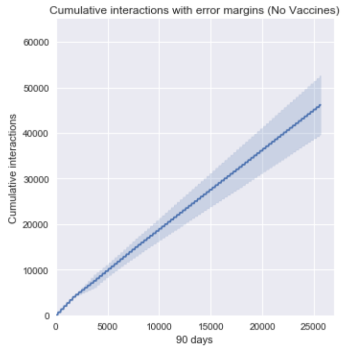
(e) Bangladesh only strategy



(f) Transmission group strategy

Figure G.16: Pattern analysis for combined parameter effects on cumulative infections of the: (a) base case (no vaccines), (b) Elderly first strategy, (c) Children first strategy, (d) Equalizing strategy, (e) Bangladesh only strategy & (f) Transmission group strategy

Figure G.17 shows the cumulative number of interactions for combined parameter testing.



(a) base case (no vaccines)

(b) Elderly first strategy

(c) Children first strategy

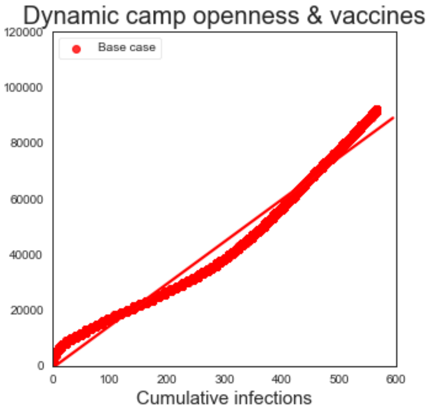
(d) Equalizing strategy

(e) Bangladesh only strategy

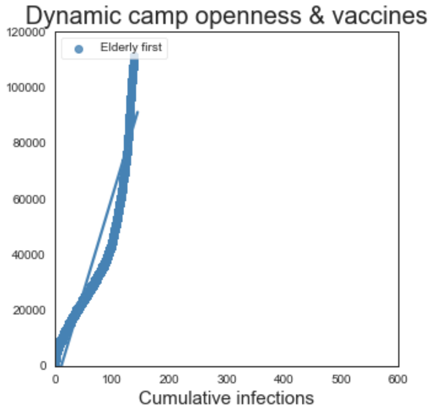
(f) Transmission group strategy

Figure G.17: Pattern analysis for combined parameter effects on cumulative infections of the: (a) base case (no vaccines), (b) Elderly first strategy, (c) Children first strategy, (d) Equalizing strategy, (e) Bangladesh only strategy & (f) Transmission group strategy

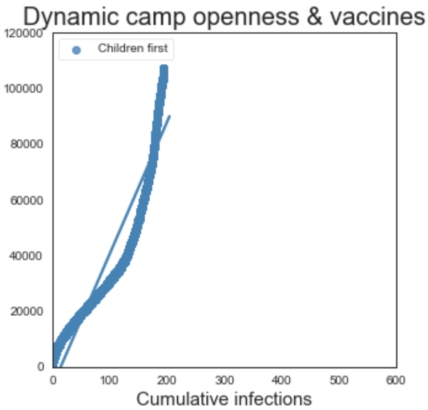
Figure G.18 shows the trade-offs between infections and interactions for five strategies.



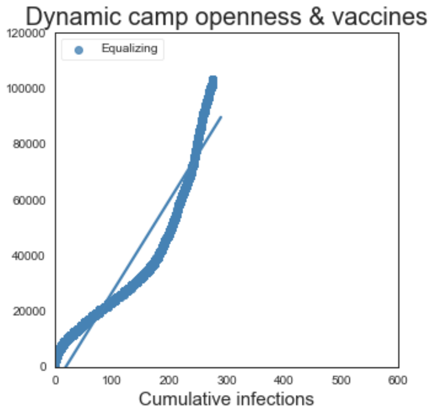
(a) base case (no vaccines)



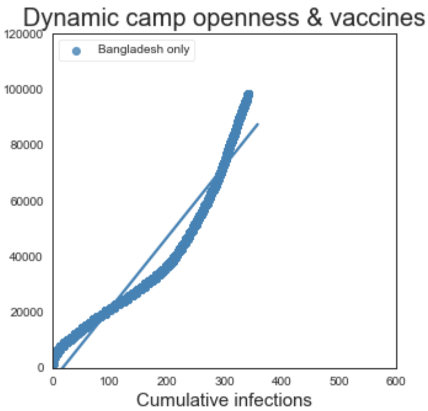
(b) Elderly first strategy



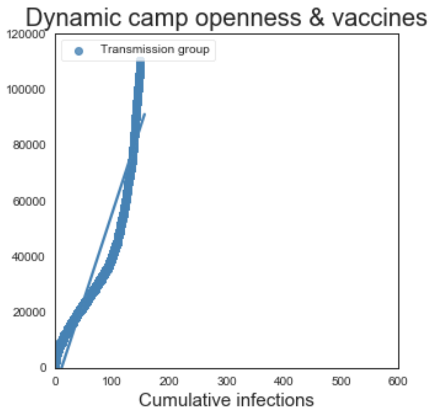
(c) Children first strategy



(d) Equalizing strategy



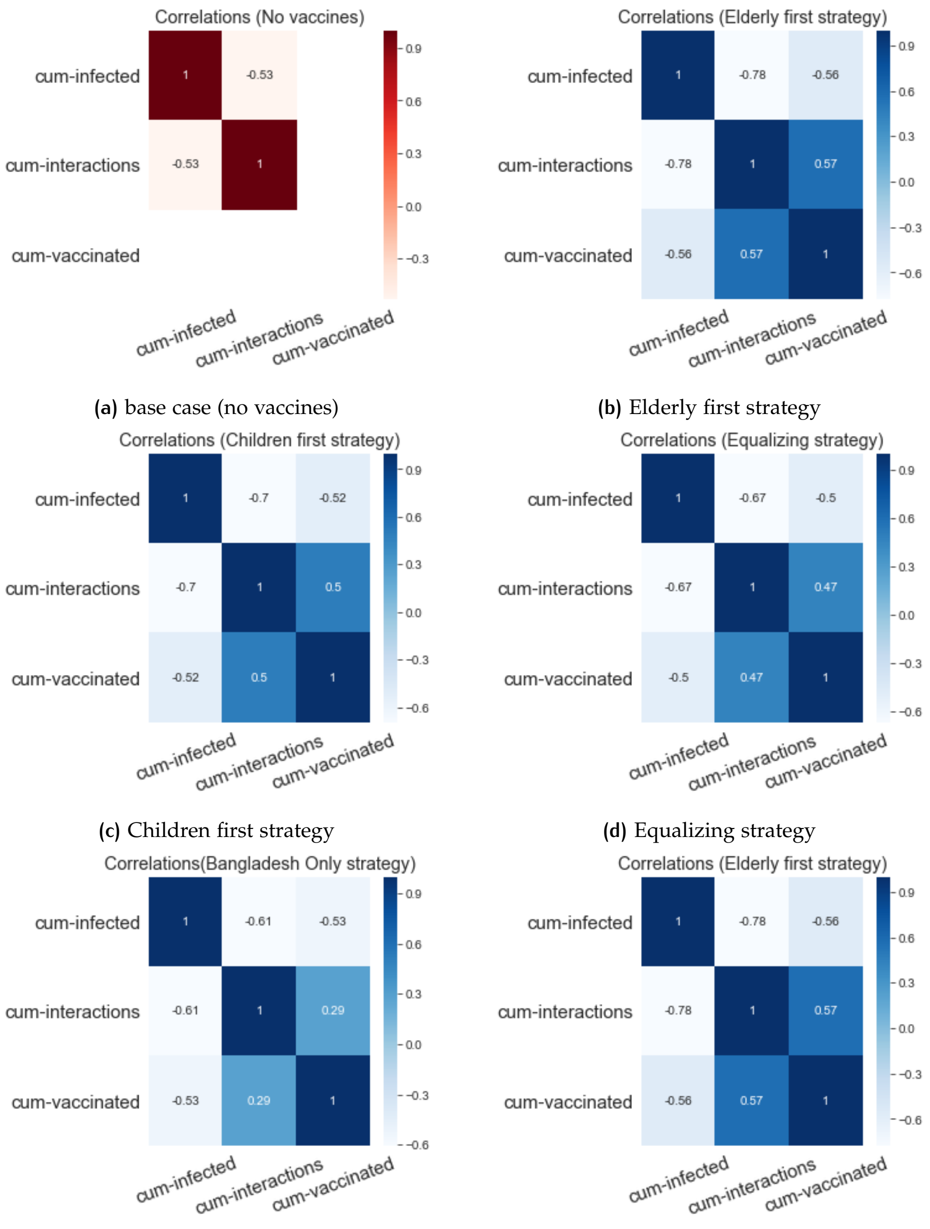
(e) Bangladesh only strategy



(f) Transmission group strategy

Figure G.18: Pattern analysis for combined parameter effects for different vaccine allocation strategies on cumulative infections & interactions for the: (a) base case (no vaccines), (b) Elderly first strategy, (c) Children first strategy, (d) Equalizing strategy, (e) Bangladesh only strategy & (f) Transmission group strategy

Figure G.19 shows the correlations for infections and interactions for 5 strategies.



(a) base case (no vaccines)
(b) Elderly first strategy
(c) Children first strategy
(d) Equalizing strategy
(e) Bangladesh only strategy
(f) Transmission group strategy

Figure G.19: Correlations between vaccines, interactions & infections for the: (a) base case (no vaccines), (b) Elderly first strategy, (c) Children first strategy, (d) Equalizing strategy, (e) Bangladesh only strategy & (f) Transmission group strategy

The results for each strategy are compared. Based on every correlation, a performance rank is created which shows the 'best-to-worst' performing vaccine allocation strategies on the dynamics between vaccines, interactions and infections. See table G.1.

Table G.1: Ranked vaccine allocation strategies on balancing interactions and COVID-19 infections

Correlations for vaccines with infections & interactions			
Rank	**Vaccine allocation strategy**	**Infections**	**Interactions**
1.	Elderly first strategy	-0.56	0.57
2.	Transmission group strategy	-0.56	0.57
3.	Children first strategy	-0.52	0.50
4.	Equalizing strategy	-0.50	0.47
5.	Bangladesh only strategy	-0.53	0.29

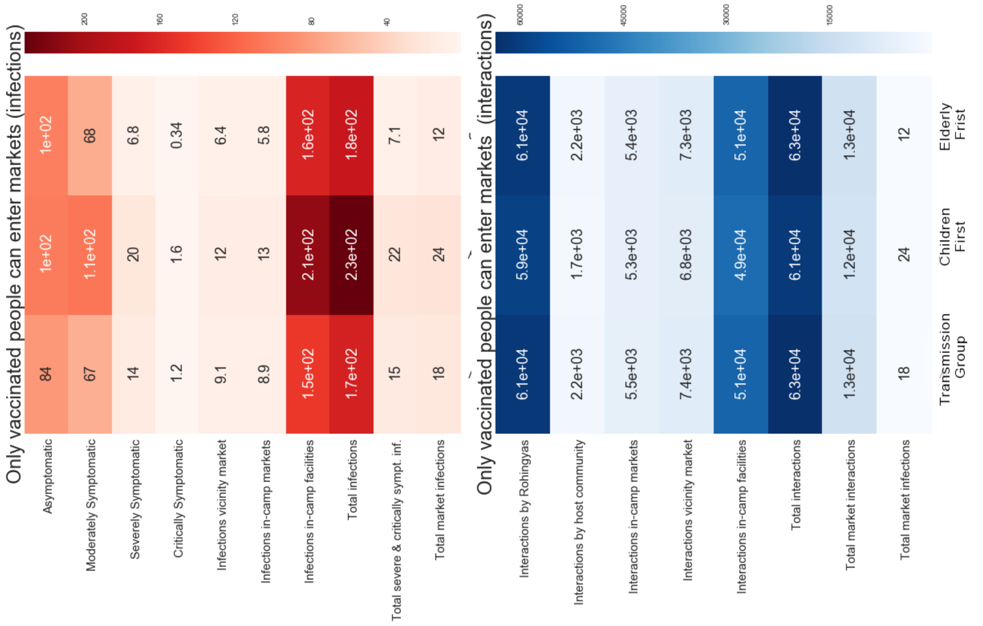
G.5 ANALYSIS ON DYNAMICS BETWEEN CAMP OPENNESS & VACCINE ALLOCATION STRATEGIES (ECONOMIC FOCUS)

G.5.1 Single effect of limited camp openness for host community & elderly

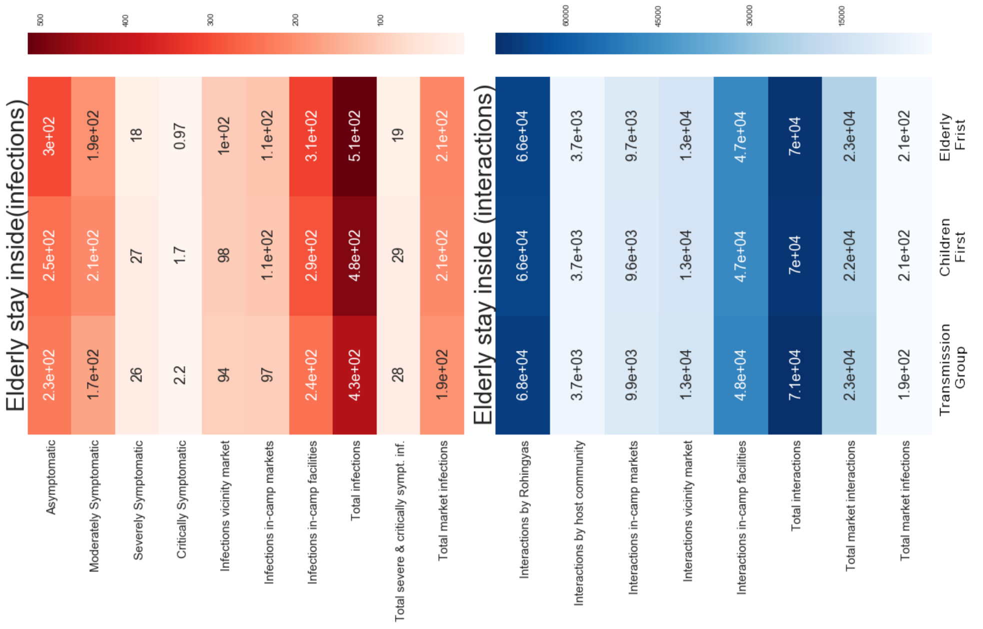
Figure **??** shows the analysis of closing camp for host community & keeping elderly home: figure G.20a shows the model results for infections and interactions if host communities are not allowed in the camp. Figure G.20b shows the same analysis, but for keeping elderly away from economic activities. These results are based on model outcomes as shown in figure G.21 and G.21. Figure G.23 shows relative effects of combined vaccine allocation strategies & dynamic camp openness.

G.5.2 Analysis of allowing vaccinated people at the markets, including and excluding host communities

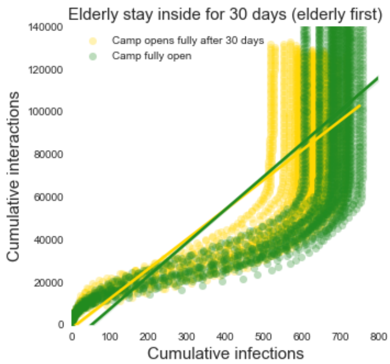
Table G.2 presents average model results for the effect of allowing vaccinated individuals to interact, including and excluding host communities. Here, vaccinated individuals are assumed to be infectious and a vaccine efficacy of 90%. These results are summarized in figures G.24a-G.24d and figure G.25.



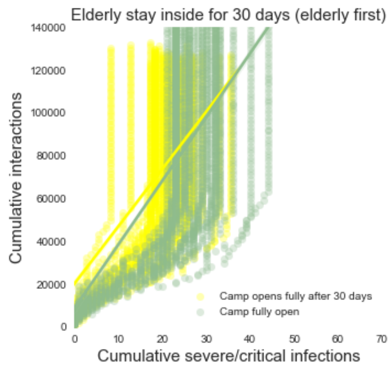
(a) Comparing three vaccine allocation strategies for closing camp for host community, vaccinated always allowed to enter



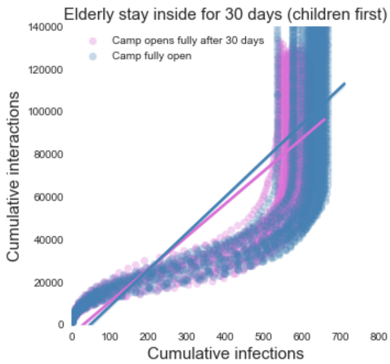
(b) Comparing three vaccine allocation strategies for keeping elderly home for 30 days, vaccinated always allowed to enter



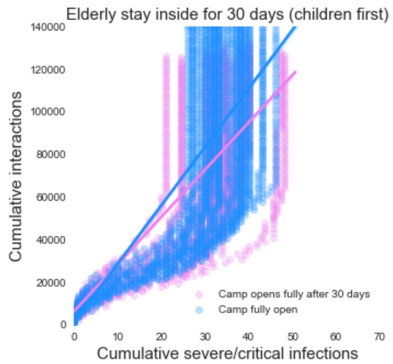
(a) Total infections (elderly first)



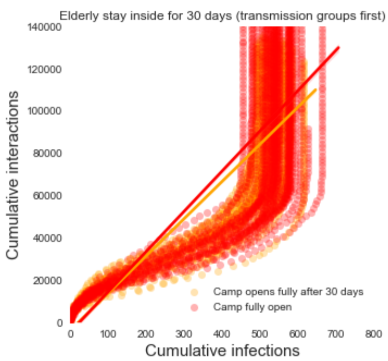
(b) Severe/critical infections (elderly first)



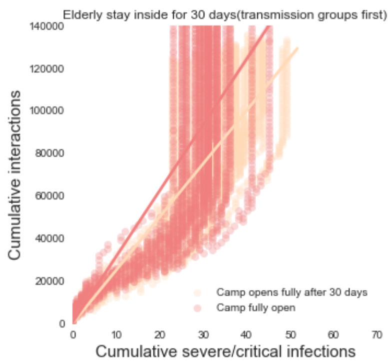
(c) Total infections (children first)



(d) Severe/critical infections (children first)

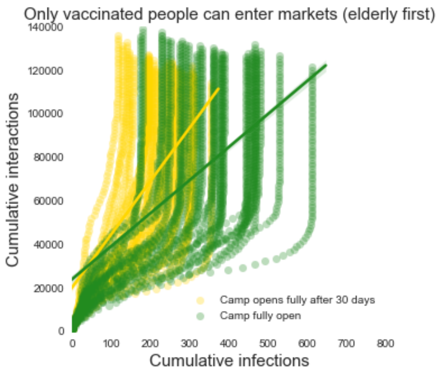


(e) Total infections (transmission group)

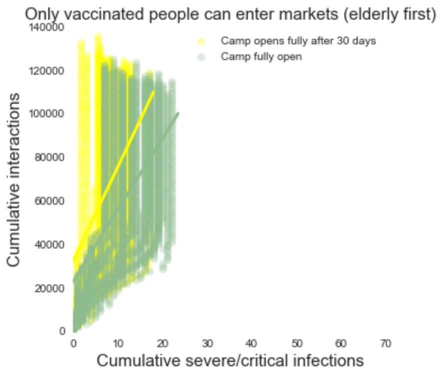


(f) Severe/critical infections (transm. GR.)

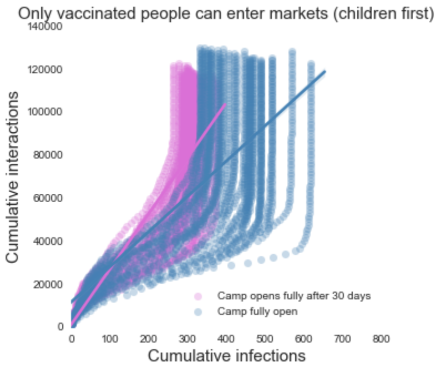
Figure G.21: [Trade-off effect between infections (left) or severe/critical infections (right) and interactions for keeping elderly home for 30 days, allow vaccinated



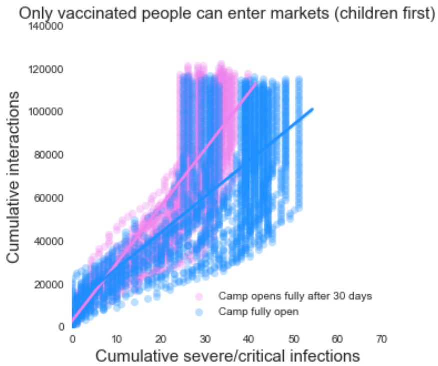
(a) Total infections (elderly first)



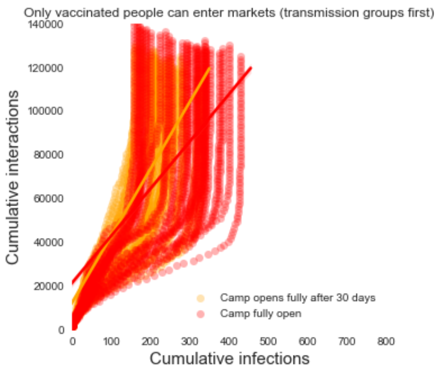
(b) Severe/critical infections (elderly first)



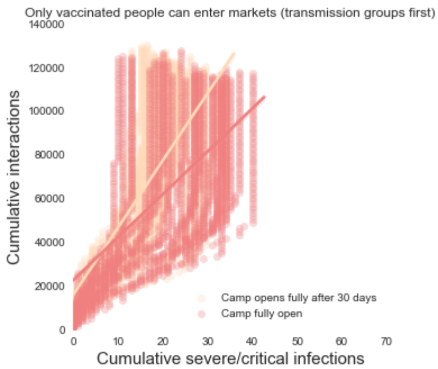
(c) Total infections (children first)



(d) Severe/critical infections (children first)



(e) Total infections (transmission group)



(f) Severe/critical infections (transm. GR.)

Figure G.22: [Trade-off effect between infections (left) or severe/critical infections (right) and interactions for closing markets completely vs. for only 30 days)

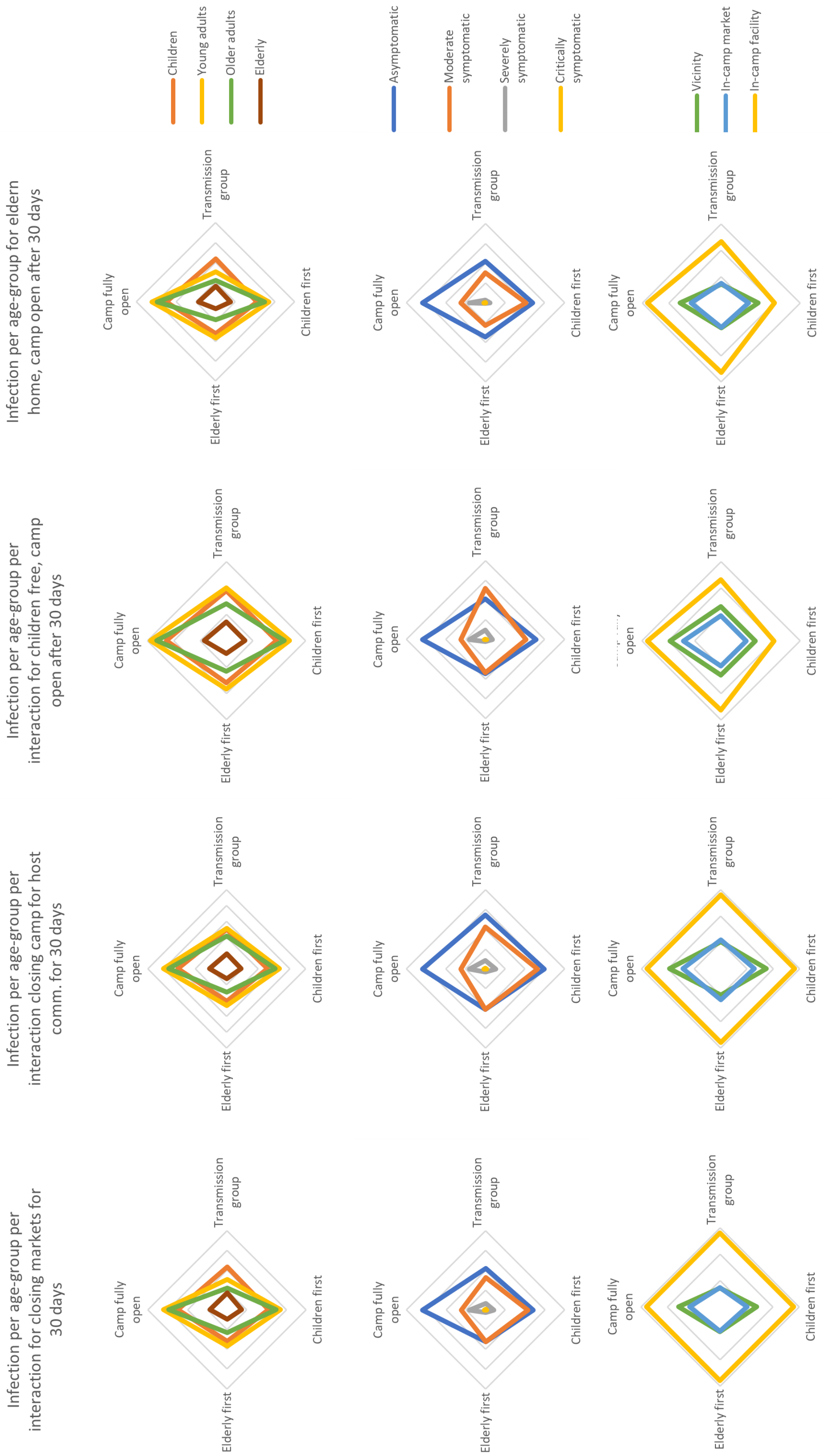
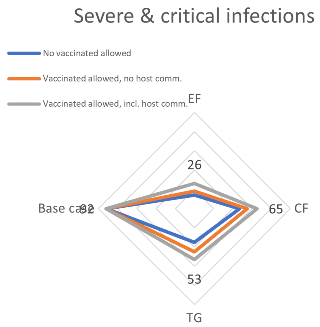
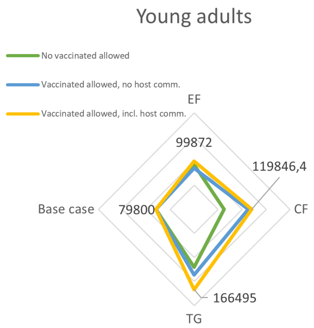


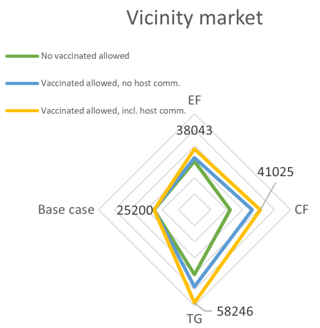
Figure G.23: Overview of model results for four types of dynamic camp openness in combination with three vaccine allocation strategies



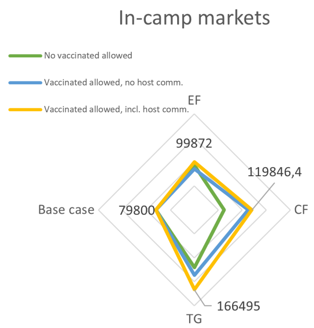
(a) Severe & critical infections



(b) Young adults



(c) Vicinity market



(d) In-camp markets

Figure G.24: Comparing strategies for dynamic market openness, unlimited access for vaccinated individuals & effect of including the host community: (a) for type of infection and interactions (b) among younger adults and at (c) the vicinity market and the (d) in-camp markets

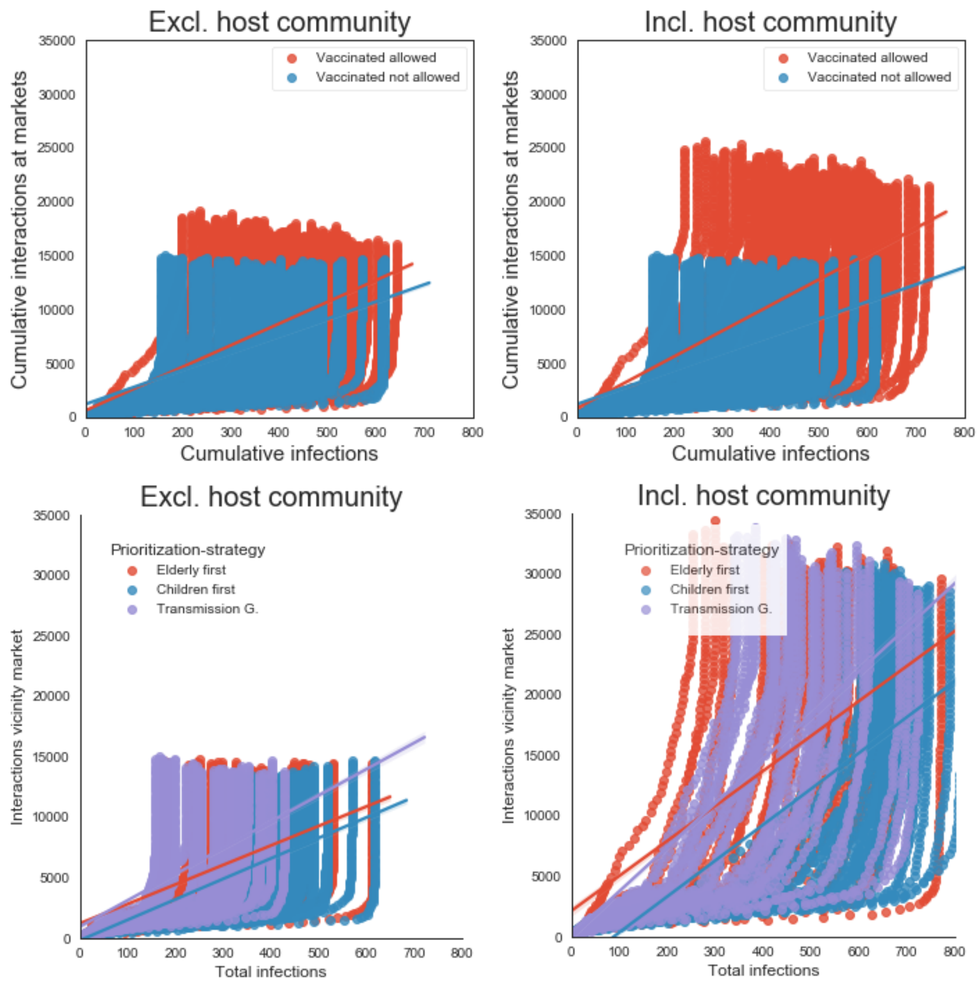


Figure G.25: Model results for always allowing vaccinated people & host communities for maximizing economic activity (600 runs)

Table G.2: Model results for always allowing vaccinated people & host communities for maximizing economic activity (600 runs)

	Experiment for more economic interactions						
	Severe/critical	**% diff.**	**Vicinity market**	**In-camp market**	**% diff.**	**Young ad.**	**% diff.**
Elderly First (excl. host com.)	14	*-85%*	30280	92485	*17%*	70011,2	*6%*
Children First (excl. host com.)	47	*-49%*	22127	62214	*12%*	83158,53	*26%*
Transmission Group (excl. host com.)	35	*-62%*	40435	120095	*53%*	81714,36	*24%*
Elderly First (incl. vaccinated, excl. host com.)	18	*-80%*	32515	85361	*44%*	73696	*12%*
Children First (incl. vaccinated, excl. host com.)	55	*-40%*	35987	112547	*41%*	91383	*39%*
Transmission Group (incl. vaccinated, excl. host com.)	45	*-51%*	48137	136471	*76%*	97279	*48%*
Elderly First (incl. vaccinated, incl. host com.)	26	*-72%*	38043	99872	*31%*	85487	*30%*
Children First (incl. vaccinated, incl. host com.)	65	*-29%*	41025	119864	*61%*	103263	*50%*
Transmission Group (incl. vaccinated, incl. host com.)	53	*-42%*	58246	166495	*114%*	117708	*79%*
Dynamic Camp Openn. (excl. vaccinated)	92	*100%*	25200	79800	*100%*	65800	*100%*

Table G.3: Model results for always allowing vaccinated people & host communities for maximizing interactions at markets

	Strategy	Sev./crit. infections	%	Market interactions	%
Vaccinated allowed, excl. host comm.	**EF**	18	*120%*	25203	*112%*
	CF	55	*160%*	31729	*141%*
	TG	45	*149%*	39605	*176%*
Vaccinated allowed, incl. host comm.	**EF**	26	*128%*	29479	*131%*
	CF	65	*171%*	34430	*153%*
	TG	53	*158%*	48156	*214%*
Base case (100%)		**92**	***100%***	**22503**	***100%***


HANDICAP
INTERNATIONAL