Reccuring COVID-19 Vaccinations

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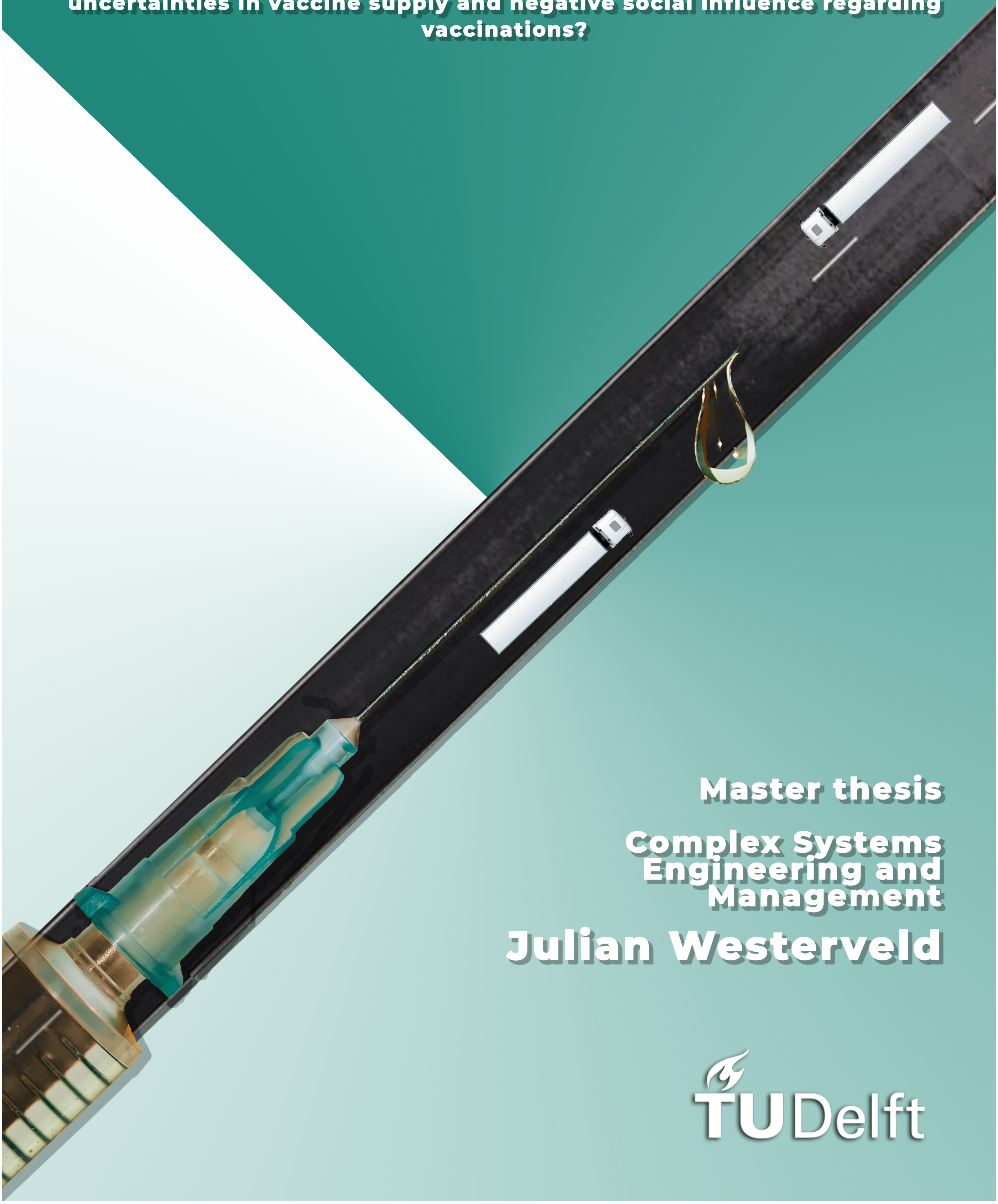

Master thesis

Complex Systems Engineering and Management

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TU Delft

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Master Thesis
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Second supervisor	Prof.dr. M.E. (Martijn) Warnier

Preface

For the last six months, I've been working on a topic that concerns all of us: vaccinations, the most important part of the exit strategy of a global health crisis. I really enjoyed the fact that I was able to do a research on such a recent topic that affects myself as well, contrary to lots of other projects that I have done during my time at TU Delft.

Although it might be too late, I want to advise all students that are reading this preface to get inspired on what to write in their own preface, to plan enough fun activities during your thesis project to get some distraction. This really helped me to bring up the motivation to work extra hard, so that I had enough time left to do some fun things.

First of all, I want to thank Alexander Verbraeck, who fulfilled the role of first supervisor for this thesis project. It was very challenging that the information about the vaccinations was constantly changing. I came up with the idea to research the topic of vaccinations, because the vaccination campaign in the Netherlands was a complete mess. However, within a couple of weeks, the Netherlands entered the top 10 of fast vaccinating countries. These developments gave me the idea that my research had become irrelevant, so I had to adapt my research multiple times. Every single time that I approached Alexander about my doubts of the relevance of my research direction, he came up with an infinite flow of ideas that were still interesting to investigate and never been researched before. This has kept me motivated throughout the entire process to successfully complete this project.

Second, I want to thank Martijn Warnier, my second supervisor, for his additional supervision on my project and the courses that he taught me over the last couple of years, which were clearly way more interesting than most of the other courses during my bachelor and master. This made me choose for this the kind of research approach that I used in this research, even before selecting the topic. In our last meeting, I was asking for things that I could improve in the last couple of days that I had left. He told me that it would be definitely worth it to spend some more time the make some improvements, but that adding some paint job on the house would not realize a substantially different house. Even if graduation projects seem perfect, they can always be improved, so when you are satisfied with the work that you have delivered, it is good enough and you have to know the moment when to stop adding extra paint jobs. And that moment is now.

Julian Westerveld
Delft, 5 july 2021

P.S. Veronique Meerdink wanted to be mentioned in this preface, but unfortunately, I have decided to leave that out.

Management summary

The duration of protection that COVID-19 vaccines provide is still uncertain (Murray & Piot, 2021). Therefore, a possible future scenario is that the entire population will need an extra dose of a vaccine. Yearly recurring flu vaccinations take place at general practices (GP), so this might also be the case for COVID-19 vaccinations. General practitioners indicate that this would not be efficient. In fact, many general practitioners don't want to execute any vaccinations, because their main job is to provide primary healthcare (Buckley, 2021). On the one hand, when considering the insights of general practitioners, the question arises whether it is desirable for GPs to take care of the vaccinations. On the other hand, immunization of an entire country is a huge operation, so it is important to know which contribution GPs can make to accomplish this task. To answer this question, the required performance of the system must be investigated. Therefore, the main research question is:

What is the required performance of the vaccination system to keep the vaccination rate above a sufficient level and minimize virus spread, given uncertainties in vaccine supply and negative social influence regarding vaccinations?

This research explores the interactions the concepts of social influence, service level (i.e. the ease of getting vaccinated) and willingness to vaccinate. Several experiments were run wherein negative social influence influences willingness to vaccinate in varying degrees. The same applies to the service level of the vaccination system, which is expressed in waiting times, vaccination speed and canceled appointments. Uncertain deliveries impacts the vaccination speed and the number of canceled appointments in a negative way. A lower average willingness to vaccinate leads to lower vaccination rate and stimulates virus spread. The minimum vaccination rate to achieve herd immunity is assumed to be 70% (Lippi & Henry, 2021). Since an epidemic and willingness to vaccinate of a population are driven by social interactions, an Agent-Based Modeling (ABM) approach was chosen to conduct this research.

Based on the findings of this research the following lessons learned have been formulated. First, it is recommended to focus on higher vaccination capacities in order to reduce the vaccination times and limit infections. Despite the fact that vaccinations can be executed more efficiently by GGDs and that many GPs are not willing to take care of vaccinations, the additional force of the GPs can be useful. Provided that they accept to spend 1 hour per day for 37 days, GPs can take care of 11% of the vaccinations. Therefore, the options should be discussed with them in order to convince them to take part in the vaccination campaign. Besides the 11% of the population that GPs can possibly vaccinate, another 89% percent of the population should be vaccinated. Therefore, re-establishment of (some of) the current mass vaccination sites would be a useful option to enable GGDs to work efficiently.

Second, this research shows that the minimal required performance of the vaccination system to keep the vaccination rate above a sufficient level is low. That indicates that the willingness to vaccinate in the Netherlands is robust. Enormous increases in negative social influence, delays and low service levels didn't cause significant disruptions of the willingness to vaccinate. Even in situations with 40% chance of delayed vaccine supplies and high values of negative social influence, the vaccination rate remains above 70%. However, it is still important take the effects of social influence and low service levels into account, because they might be stronger when the willingness to vaccinate is lower. That will possibly be the case when we are not in a crisis situation anymore.

Suggestions for further research are making improvements in the model and investigating the actual importance of social influence on vaccination decision making. The last suggestion is to conduct experiments with the model proposed in this research, with the amount of patients that currently receive an influenza vaccination, instead of the entire population. With those experiments, it can be evaluated to what extent GPs can take care of the vaccinations when the number of patients is equal to the number of people that already visit the GP for a vaccination every year.

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1. Introduction

Vaccination programs are regularly recurring events, in order to prevent the spread of infectious diseases. Vaccinations protect against infections in seasonal epidemics, sudden epidemics, infections of foreign local viruses or children diseases. A very recent example is the global COVID-19 pandemic. The COVID-19 pandemic has put countries in lockdown to slow down infections, therefore lowering pressure on health care and protect vulnerable groups. The intensive care departments in the hospitals are overloaded and a lot of regular healthcare is being postponed. The RIVM estimated 50.000 healthy living years were lost as a result of non-executed regular healthcare, while only 13.000-21.000 healthy living years were saved due to the measures (Van der Hoeven, 2020). Economic activity decreased and the population is restricted in their freedom. The estimated economic decline in the Netherlands is 4.3% (BNR, 2020). The costs of support measures packages caused a public deficit of 68 billion euros, contrary to the pre-crisis estimated surplus of 2 billion euros.

The first COVID-19 inoculation in the Netherlands was done in January (NOS, 2021a). At that time, the vaccines by pharmacists Pfizer/BioNTech and Moderna were to only two that were already approved by the European Medicines Agency (NOS, 2021c). However, the availability of a vaccine is not enough. Successful vaccination campaigns are impossible without good logistics (Duijzer et al., 2018). Distribution among the population was the next step, but nothing indicated that the Netherlands was ready for vaccinating, because the strategy that the RIVM intended to deploy was still unclear (Fransoo, 2020).

A lot of complexities are involved in this vaccination program, caused by its massive scale, uncertainty in delivery of vaccines and high spreading rate due to quick mutation capabilities of the coronavirus (Shariare et al., 2021). Another significant challenge of this vaccination program is that the vaccines presumably must be transported and stored under highly cooled conditions, to ensure their shelf lives. The Pfizer vaccine, for instance, is based on RNA and must be stored at -70 degrees Celsius (NOS, 2020). This, combined with the huge amounts of vaccines that need to be transported to a lot patients require major innovations on existing vaccine supply chains (De Bok, 2020).
Since the development of the virus is uncertain and setbacks in vaccine deliveries occurred, it was hard to make the system perform under different circumstances and adapt to weekly changes in vaccination strategies (Van der Veen, 2021).

In the meantime, the vaccination campaign in the Netherlands is ongoing at a fast pace and the willingness to vaccinate of the Dutch population is still increasing (Herter, 2021; Zwolsman, 2021). However, after completing vaccination of the population, we might not be finished yet. It is likely that vaccinations will remain necessary in the future for vulnerable groups, or even the entire population (Hodes & Majeed, 2021). The duration of protection of the vaccines is still uncertain and new vaccinations might be needed to immunize people against new virus variations (Murray & Piot, 2021). For that reason, the Dutch government ordered enough vaccines for 2022 and even a part of 2023 (Rijksoverheid, 2021). Therefore, scenario that the entire population needs extra doses of vaccines in the next couple of years is not unimaginable. It is unclear how mass vaccinations will take place again, when we are not in a crisis situation, without the mass vaccination sites in their current form.

On the one hand, it is very important that a sufficient vaccination rate will be met for immunity purposes. People's attitude towards vaccination can be influenced by others and people's willingness to get vaccinated might decrease if the service level of the system is low. Service level is determined by the ease of getting vaccinated, i.e. travel distance, waiting time and personal contact with general practitioners (De Vries, 2021). On the other hand, the vaccination campaign should be executed quick enough to prevent an excessive increase of infections.

Since flu vaccinations in the Netherlands take place at general practices (GP), it is a possible scenario that future COVID-19 vaccinations will take place at general practices. General practices have limited

space, so they cannot receive many patients at a time, considering social distancing measures (Stad, 2021).
According to Fränk Ritter, a general practitioner in Rotterdam, 4 patients per hour can be injected at the general practice. Doctor Ritter mentioned that vaccinations can take place more efficiently through the municipal health service (GGD). Another general practitioner, doctor Buckley states that general practitioners should not execute any vaccinations at all, because he considers vaccinations not as his task. Providing primary healthcare is the job of a general practitioner. And he shares this opinion with a lot of other general practitioners.

On the one hand, when considering the insights of general practitioners, the question arises whether it is desirable for GPs to take care of the vaccinations. On the other hand, immunization of an entire country is a huge operation, so it is important to know which contribution GPs can make to accomplish this task. To answer this question, the required performance of the system must be investigated. Therefore, the main research question is:

What is the required performance of the vaccination system to keep the vaccination rate above a sufficient level and minimize virus spread, given uncertainties in vaccine supply and negative social influence regarding vaccinations?

The following sub research questions are formulated to contribute to the answer on the main research question:

1. What is the impact of uncertain vaccine deliveries on the time to get the population vaccinated and the vaccination rate?

The duration of the vaccination campaign is a Key Performance Indicator of the system. A long period of vaccinating causes two effects: a longer period for the virus to spread among the population and a longer period for people to (possibly negatively) influence each other on their willingness to vaccinate. Especially when the vaccines need to be produced on a massive scale, the deliveries of vaccine batches might be uncertain.

2. What is the impact of negative social influence on the vaccination rate?

Spreading positive information and sharing supportive evidence at the right time can improve the vaccination coverage in a social network (Ni et al., 2021). From their simulations, it was evident that the strength of social interactions among individuals has a considerable impact on vaccine coverage. By obtaining insights in the impact of social influence on the vaccination rate, it becomes clear how important it is to maintain a proper service level to prevent spreading of negative experiences. In addition, the importance of vaccinating quickly can be determined. Vaccinating very quickly constrains the time to spread negative information and prevents an eventual decrease in willingness to vaccinate.

3. What is the impact of the service level of the vaccination system on the vaccination rate?

Service level is determined by the ease of getting vaccinated, i.e. travel distance, waiting time and personal contact with general practitioners (De Vries, 2021). If the service level has a great impact on the vaccination rate, it is important to maintain a proper service level.

4. Under which circumstances of service level, negative social influence and uncertain deliveries will the vaccination rate drop to an insufficient value to achieve herd immunity?

Uncertain deliveries can lead to a decrease in service level, which increases negative experiences. When social influence appears to have a large impact on vaccination rate, a drop in vaccination rate can be the outcome of uncertain deliveries and not being able to meet people's demanded service levels. The minimal conditions of service level, given social influence and the uncertainty in vaccine deliveries determines the performance that the system must deliver to prevent a revival of the virus and a decrease in vaccination rate. According to (Lippi & Henry, 2021), the threshold for achieving herd immunity for COVID-19 is around 70% of the population.

5. Which contribution can GPs make to the vaccination campaign, given the minimum required system performance to achieve herd immunity?

However executing vaccinations is absolutely not the main task of general practitioners (Buckley, 2021), vaccinations at the GP already occur and vaccinating an entire country is a huge operation, so the help of GPs might be useful. By evaluating which capacities are needed to achieve a sufficient vaccination rate and limited spread of the virus, the contribution of GPs can be calculated, given the time that a GP would accept to spend on vaccinations. With this insights, it can be considered by policy makers to what extent GPs can be deployed as additional forces to the vaccination campaign.

This research is exploratory and focuses on getting insights in the required system performance and the interactions between willingness to vaccinate, service level and social influence.

An existing neighborhood was used as a case study, in order to represent a realistic situation. The selected neighborhood is Oude Westen in Rotterdam, the Netherlands. Oude Westen is a located in the city center of Rotterdam. The neighborhood has about 9500 inhabitants. The composition of the population is diverse: singles, families with children and students live there. Residents and visitors describe Oude Westen as multicultural, diverse and lively (Gemeente Rotterdam, 2020). A more extensive description of Oude Westen is provided in section 3.2.

An Agent-Based Modeling (ABM) approach was chosen to conduct this research. ABM has been widely used to study topics regarding the COVID-19 pandemic and is useful, because an epidemic and willingness to vaccinate of a population are driven by social interactions. The suitability of this modeling approach will be further elaborated in section 3.3.

The structure of the report is as follows: in chapter 2, a literature review is presented, followed by the identification of a knowledge gap. Chapter 3 explains how the simulation model is constructed. Chapter 4 contains the experimental setup, followed by chapter 5 wherein the results are analyzed and discussed. The discussion and limitations can be found in chapter 6. The conclusions, policy recommendations and suggestions for further research are presented in chapter 7.

2. Literature Review

In this chapter, a literature review will be presented. This literature review was used to obtain insights in what has already been researched and identifying a knowledge gap. The literature review will be introduced in section 2.1. The identified knowledge gap will be presented in section 2.2.

2.1 Literature Review

The approach of this literature review is two-fold. The first part of the literature review is about the entire vaccine supply chain from manufacturers to the people, to get an idea of the bigger system in which the vaccination distribution exists. By obtaining insights in the entire vaccine supply chain, difficulties and challenges that possibly affect the vaccination distribution can be identified.
Second, literature about the COVID-19 pandemic, vaccinations, social influence on vaccination decisions and how Agent-Based Modeling is used for research in these topics was investigated, in order to gather the information that is used in the model and identifying a knowledge gap.

In section 2.1.1, a brief explanation of the method that was used to conduct the literature review is provided.

2.1.1 Method

To conduct the literature review, online searches were conducted on Scopus and Google Scholar. The keywords that were used to find literature about vaccine supply chains, uncertainty and vaccination strategies, social influence and the use of ABM for COVID-19 are presented in Table 1.

Table 1: Keywords

Vaccine supply chain	Uncertainty	Vaccination strategy
Supply chain	Cold chain	Logistics
Distribution	Immunization	COVID-19 vaccine
Vaccination Campaign	Vaccination strategies	Transportation
Agent-based Modeling	Willingness to vaccinate	Vaccinations

Using combinations of these keywords resulted in a couple of relevant articles. The selection of relevant articles was done by reading the titles and abstracts. Relevant articles were stored in the Mendeley reference manager. Most of the literature was found by "snowballing" i.e. deriving articles from the reference lists of relevant literature (Wee & Banister, 2016).

2.1.2 Discussion of the literature

The topics in the literature that will be discussed in this section are uncertainty, vaccination strategies, supply chain alignment and cold chain capacity, in order to get an overview of the bigger system in which the vaccination distribution exists. Thereafter, the use of ABM for COVID-19 research and social influence on vaccination decisions will be discussed.
The basis of understanding the vaccine supply chain is to distinguish its four components. The vaccine supply chain consists of four components: product (what type of vaccine is needed?), production (how many vaccines should be produced and when?), allocation, who should receive the vaccine?), and distribution (how should the vaccine be distributed?) (Rastegar et al., 2021). The image below shows an overview of the vaccine supply chain. Duijzer et al. (2018) described a couple of similarities of the vaccine supply chain relative to other supply chains. They also reported some unique characteristics of vaccine supply chains.

	Product	Production	Allocation	Distribution
	What kind of vaccine should be used?	**How many doses should be produced and when?**	**Who should be vaccinated?**	**How should the vaccines be distributed?**
	Right product (decision)	*Right product (realization), Right time*	*Right place (decision)*	*Right place (realization), Right time*
Similarities	- Product development (R&D)	- Long production time - Uncertain demand - Pull process: initiated by the customer (i.e., public health organisation) - Uncertain yields		- Inventory control - Facility location - Routing - Supply chain design - Perishable product - Temperature controlled chain
Unique characteristics	- Decentralized decisions: product is determined by public health organizations, not by the supplier - Public health organizations are non-profit, whereas supplier is for-profit - Product changes very frequently (yearly for annual influenza vaccine) - Product decision is made under time pressure and high demand uncertainty	- Demand externalities due to disease dynamics and the protective power of vaccinations for non-vaccinated people	- Complex decision making: political interests, equity considerations - End customer (i.e., `patient') does not pay for the product in most cases - Push process: initiated and performed in anticipation of end customer need - Decentralized decisions: end customer has no power in this phase	- Mass distribution under time pressure

Figure 1: The vaccine supply chain (Duijzer et al., 2018)

2.1.2.1 What is uncertainty?

Decision making under uncertainty means that decisions are made when only partial or imperfect is available (Roy, 2005). This is applies to the COVID-19 situation, because of three reasons. First, the effectivity and safety of the vaccines for different age groups is not evaluated as extensively as in non-crisis situations, because of limited time. Therefore, allocations decisions are made under uncertainty and the allocation strategy could therefore change every week, based on new available information. Second, the delivery of the vaccines is uncertain because of the scarcity, negotiations between countries and pharmacists and lack of experience in producing this particular type of vaccine, since the vaccines are newly introduced. Last, the virus continuously mutates, so that entails uncertainty in the infectivity of the virus and the susceptibility of new mutations to the vaccines. This could also suddenly change the vaccination strategy.
There are three types of uncertainty that may be distinguished when partial information is available (Lempert et al., 2006). First, randomness, that is characterized by random variables related to business-as-usual operations. Second, hazard, that refers to low-probability high-impact unusual events. Third, deep uncertainty, under which the information available is not sufficient to estimate an objective or subjective probability for these scenarios (Klibi et al., 2010).

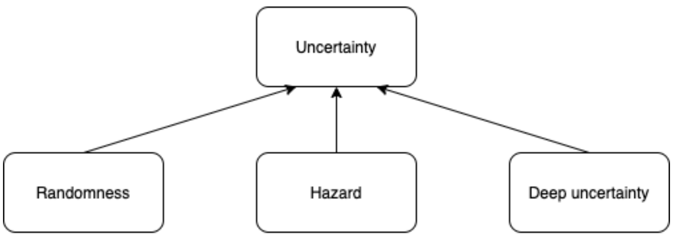


Figure 2: Types of uncertainty

2.1.2.2 Vaccination strategies

Different vaccination strategies could have an impact on supply chains. Therefore, literature was searched about suitable vaccination strategies. The objective in the optimal allocation is to minimize the number of new infections (Duijzer et al., 2018). However, the Dutch government decided to first vaccinate the most vulnerable groups, rather than groups who are more likely to transmit the virus. Goldstein et al. (2009) have found that the top priority in an allocation of a sizeable quantity of seasonal influenza vaccinations goes to young children (0-6), followed by teens (14-18), then children (7-13). The explanation for this is that children have a high probability of transmitting the virus because of their close contact and after infection, they are likely to infect their parents, which will form a bridge to the rest of the population. This is also confirmed by Dalgıç et al. (2017) and Medlock & Galvani (2009).
Lee et al. (2015) state that the best strategy to contain a pandemic is to give priority to higher risk population groups. However, the more transmissible the virus is, the lower the threshold for switching to nonprioritized groups.
Mylius et al. (2008) make a distinction between the situations where a vaccine is available from the beginning of a pandemic and when the vaccine becomes available during an ongoing pandemic. Their suggestion is to vaccinate school children when the vaccine is available from the start of a pandemic and prioritize individuals with high-risk of complications if a vaccine becomes available during the pandemic. The last allocation strategy is more in line with the strategy that the Dutch government deployed.

Composition decisions have to be made under time pressure. The combination of time pressure and extreme uncertainty, which is especially the case for sudden outbreaks, makes the decision making processes complex. Future research should focus on these aspects to help decision makers in uncertain situations (Duijzer et al., 2018). Duijzer et al. (2018) confirm that a gap in the literature exists in the first components of the supply chain, product and production. Those components are the cause of the difficulty involved in designing a robust distribution design, because the vaccination strategy probably changes from week to week. The strategy is not straightforward and static, because of uncertainties in delivery (production component) and suitability and safety for different population groups (product component).

2.1.2.3 Supply chain alignment

There will be a shortage on storing and transporting capacity in multiple parts of the supply chain. However, it is not clear yet how much capacity is needed in which part of the supply chain (Weintraub et al., 2020). According to Rastegar et al. (2021), the four components of the supply chain are product, production, allocation and distribution. The distribution of the vaccine depends on the other three components, because the distribution depends on vaccine characteristics, availability and logistic requirements for vaccinating different population groups (Duijzer et al., 2018). The European Union (2020) published a vaccination strategy factsheet, wherein they present a guideline for member states to prioritize vulnerable groups, including health care workers, people over sixty years, people with underlying health issues, essential workers, people who cannot socially distance and disadvantaged socio-economic groups. The allocation of vaccines to these groups and they order of vaccinating will have an impact on the supply chain because vaccinating different groups involves different requirements. This impact of vaccination strategy is not well described in the literature and needs to be researched.
In order to achieve an efficient supply chain, a design should be developed so that the different components are properly coordinated. The design of the supply chain is both qualitative and quantitative. Vaccine supply chains have been studied from qualitative perspective (Dai et al., 2021), but a quantitative study is important to get insight in how capacities must be aligned with each other and where the bottlenecks will occur. This will be especially important for the alignment of the production and the other components of the vaccine supply chain. The qualitative part refers to the logistics design that consists of locating vaccination points, hubs and storage locations (Duijzer et al., 2018).

2.1.2.4 Cold chain capacity

A general statement that is often mentioned in the literature is the need for increased cold chain capacity (Hyde et al., 2012; Kendal et al., 1997; Lloyd & Cheyne, 2017; Rahi & Sharma, 2020; Weintraub et al., 2020; Weir & Hatch, 2004; Zaffran et al., 2013). Refrigeration lapses are a major cause of vaccine wastage (Setia et al., 2019). News items often mention that the fact that there are a lot pieces of the logistic puzzle that need to be filled in. As well as the literature, ensuring the cold environment during transport and storage is reported as the most difficult challenge. But why is this such a big challenge? There already exist suitable methods to maintain low temperatures, like the use of dry ice (Kendal et al., 1997; Stikkelorum, 2020). Logistiek.nl (2020) reports 4 potential barriers that complicate the transportation under cold conditions. First, air cargo companies have some experience with cooled transportation, but they lack of experience on freezing environments. A drawback of dry ice is that it adds a lot of extra weight to an aircraft, at the expense of capacity. Second, there is a limited amount of airports that can guarantee a temperature of -18C or lower for storage. Furthermore, the storage capacity on these airports is not fully available for vaccines, because the rooms are already in use. Third, monitoring of temperatures in the entire supply chain is very difficult, since there are few intercontinental integrated supply chains. Temperature fluctuations can be disastrous for the quality of the vaccines. Last, the last-mile distribution is a potential killer of the vaccine quality. The difficulties of cooling capacity, stable temperatures and monitoring also apply on local warehouses, hospitals and drug stores (De Weerd, 2020).
These challenges are mainly complicated. However, the COVID-19 situation is, contrary to most logistics problems, not complicated but complex. A complicated system can be difficult, but is predictable. A complex situation is not predictable, and therefore not a suitable subject to be optimized. Developments in the COVID-19 vaccination campaign are not predictable, because the following uncertainties are involved: which vaccine is available when, which vaccine is suitable for who, which impact do mutations have on the effectivity of vaccination, in which order should the population be vaccinated, what will the demand be and which logistics requirements, such as batch sizes and transportation temperatures, should be met (Van der Veen, 2021). These uncertainties are shown in Figure 3.

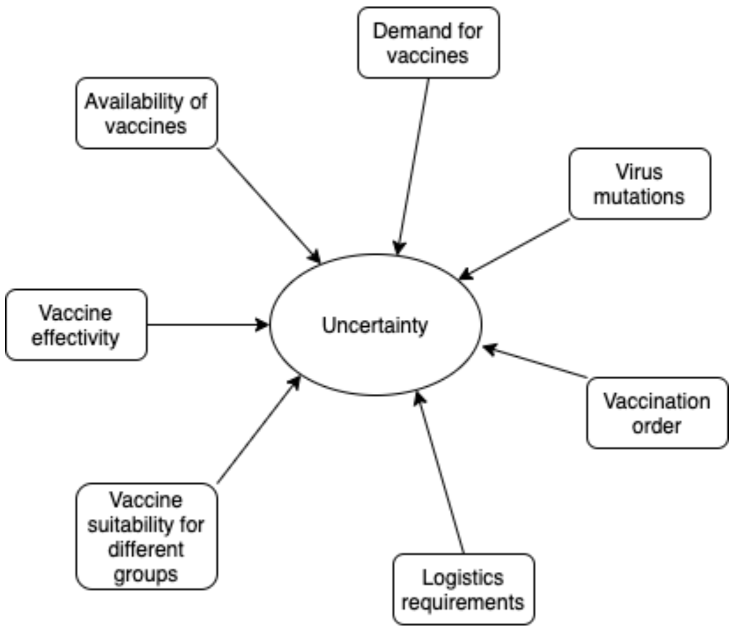


Figure 3: Causes of uncertainty

2.1.2.5 Agent-based modeling for COVID-19 research

Agent-Based Modeling (ABM) has been used for different purposes in researching the COVID-19 pandemic. Silva et al. (2020) developed an ABM to simulate the dynamics of the COVID-19 pandemic and the economic effects of social distancing interventions. According to their literature review, previous works that used the ABM approach were about testing policies, strategies for reopening public buildings, hypothetical effective treatments and spatio-temporal strategy for vaccination.
Hunter & Kelleher (2021) adapted an ABM for the spread of measles to COVID-19. They used the measle level vaccinations and immunity and found that school closures resulted in a greater decrease of infections than vaccinations. This is explainable by the fact that children have a lot of contacts at school and they might be infections before showing symptoms. Similar conclusions are drawn by Li & Giabbanelli (2021). They assumed that higher vaccine compliance will lead to lower overall infections, but that was not the case in all scenarios. The reason for this surprising behavior is a combination of factors. Vaccines are strictly administered in decreasing order of age, while older people are going neither to work or school. Hence they have fewer social contacts than younger people and their impact on preventing the spread of the virus is limited.
Jahn et al. (2021) did an ABM evaluation of vaccination strategies, considering limited vaccination capacities. The main finding of this research is that prioritizing elderly and vulnerable people minimizes hospitalizations and deaths. Moghadas et al. (2021) investigated the effectiveness vaccination by delaying second doses, in order to immunize more people with a first dose faster. Their results show that a delay of at least 9 weeks for the Moderna vaccine could maximize vaccination program effectiveness and causes a decrease in infections, hospitalizations and deaths. However, no clear advantage of delaying the second dose was found for the Pfizer vaccine.

2.1.2.6 Social influence on vaccination decisions

Several studies (Fournet et al., 2018; Larson et al., 2014; Smith et al., 2011) have suggested that factors such as safety of vaccines, severity of diseases and information from healthcare professionals influence an individuals' intention to vaccinate. Limited research has been conducted on analyzing how individuals' vaccine acceptance decisions are made from their beliefs and judgements of influential factors (Ni et al., 2021). From their simulations, it was evident that the strength of social interactions among individuals has a considerable impact on vaccine coverage.

2.1.2.7 Higher service level for hesitant people

Strategies that make vaccination easy can be effective to reach people who remain hesitant, deliberative or indifferent (Eshun-Wilson et al., 2021). Eshun-Wilson et al. (2021) found that on average the public prioritized ease, preferring single to two dose vaccinations, vaccinating once rather than annually and reduced waiting times at vaccination sites were the primary preference drivers. In line with these findings, the GGD took some measures in the Netherlands to reach hesitant people. They deployed mobile vaccination sites in order to decrease the traveling distance for people in neighborhoods with a low average willingness to vaccinate (NOS, 2021b).

In section 2.2 the findings from the literature will be summarized and knowledge gap that was identified will be introduced.

2.2 Knowledge gap

There is a lot of literature on supply chain network design, supply chain modeling and vaccination strategies. Several social studies have been conducted towards willingness to vaccinate (for example; Mouter et al., 2020 and RIVM, 2021) and different measures have been taken for target groups with a low willingness to vaccinate, in order to increase the ease of getting vaccinated (NOS, 2021b). However, the interactions of the concepts of willingness to vaccinate, social influence and service level have not been combined in simulation study yet.

It is likely that vaccinations will remain necessary in the future for vulnerable groups, or even the entire population (Hodes & Majeed, 2021). The duration of protection of the vaccines is still uncertain and new vaccinations might be needed to immunize people against new virus variations (Murray & Piot, 2021). For that reason, the Dutch government ordered enough vaccines for 2022 and even a part of 2023 (Rijksoverheid, 2021). Therefore, scenario that the entire population needs extra doses of vaccines in the next couple of years is not unimaginable. It is unclear how mass vaccinations will take place again, when we are not in a crisis situation, without the mass vaccination sites in their current form.

Since flu vaccinations in the Netherlands take place at general practices, it is a possible scenario that future COVID-19 vaccinations will take place at general practices. General practices have limited space, so they cannot receive many patients at a time, considering social distancing measures (Stad, 2021).
On the one hand, it is very important that a sufficient vaccination rate will be met in order to achieve herd immunity. People's attitude towards vaccination can be influenced by others (Ni et al., 2021) and people's willingness to get vaccinated might decrease if the system is poorly organized. For that reason, municipal health services take some measures to increase the ease of vaccinating (NOS, 2021b).
On the other hand, the vaccination campaign should be executed quick enough to prevent new outbreaks.

This research focuses on getting insights in the required system performance and the interactions between willingness to vaccinate, service level and social influence. However executing vaccinations is absolutely not the main task of general practitioners (Buckley, 2021), vaccinations at the GP already occur and vaccinating an entire country is a huge operation, so the help of GPs might be useful. By evaluating which capacities are needed to achieve a sufficient vaccination rate and limited spread of the virus, the contribution of GPs can be calculated, given the time that a GP would accept to spend on vaccinations. With this insights, it can be considered by policy makers to what extent GPs can be deployed as additional forces to the vaccination campaign.

Agent-Based modeling has been widely used to study topics regarding the COVID-19 pandemic and is useful for this research purpose, because an epidemic and willingness to vaccinate of a population are driven by social interactions. The suitability of this modeling approach will be further elaborated in section 3.3.

In chapter 3, the model will be introduced.

3. Model

In this chapter, the model will be introduced. The context in which the vaccination systems exists is discussed in section 3.1. Thereafter, the environment that is modeled is presented in section 3.2. Section 3.3 explains the choice for the agent-based modeling approach. Section 3.4 contains the model conceptualization, followed by the model specification in section 3.5. Section 3.6 provides an overview of the model interface. Section 3.7 summarizes the verification experiments and section 3.8 discusses the model validation.

3.1 Context

Before introducing the model itself, the context in which the system operates is outlined, in order to clarify which part of the supply chain the model focuses on.

3.1.1 Vaccination sites

During the COVID-19 pandemic, there are five different types of vaccination locations in the Netherlands. Most of the vaccinations take place at big GGD vaccination sites. The other vaccination sites are hospitals, general practitioners, mental healthcare institutions and elderly care institutions. People who are not able to travel to a vaccination site will be vaccinated by their general practitioner at home. The division of vaccination sites per group, not working in the healthcare sector, is presented in Table 2.

Table 2: Population groups and vaccination location

Group	Vaccination site
Age 65+	GGD vaccination site
Age 60 - 64	General practitioner
Age 18 - 59	GGD vaccination site General practitioner Hospital / General practice center
High medical risk	Hospital / General practitioner
Residents of nursing homes	General practitioner / Institution doctor
People with an intellectual disability in an institution	General practitioner / Institution doctor
Residents of small-scale residential forms	General practitioner / general practice center
Inpatient mental healthcare clients	Institution doctor
People who are not able to travel to the vaccination sites	Home, by general practitioners

3.1.2 Overview supply chain

A schematic overview of the supply chain is shown in Figure 4. The vaccine batches enter the Netherlands by airplanes. From the airport, the vaccine are transported to local storage facilities across the country by special refrigerated trucks. Afterwards, the transport proceeds to the different vaccination sites, where people will be vaccinated. For people who are not able to travel to the vaccination sites, there is an extra step in the supply chain involved. The general practitioners have to take some vaccines to those people's homes.

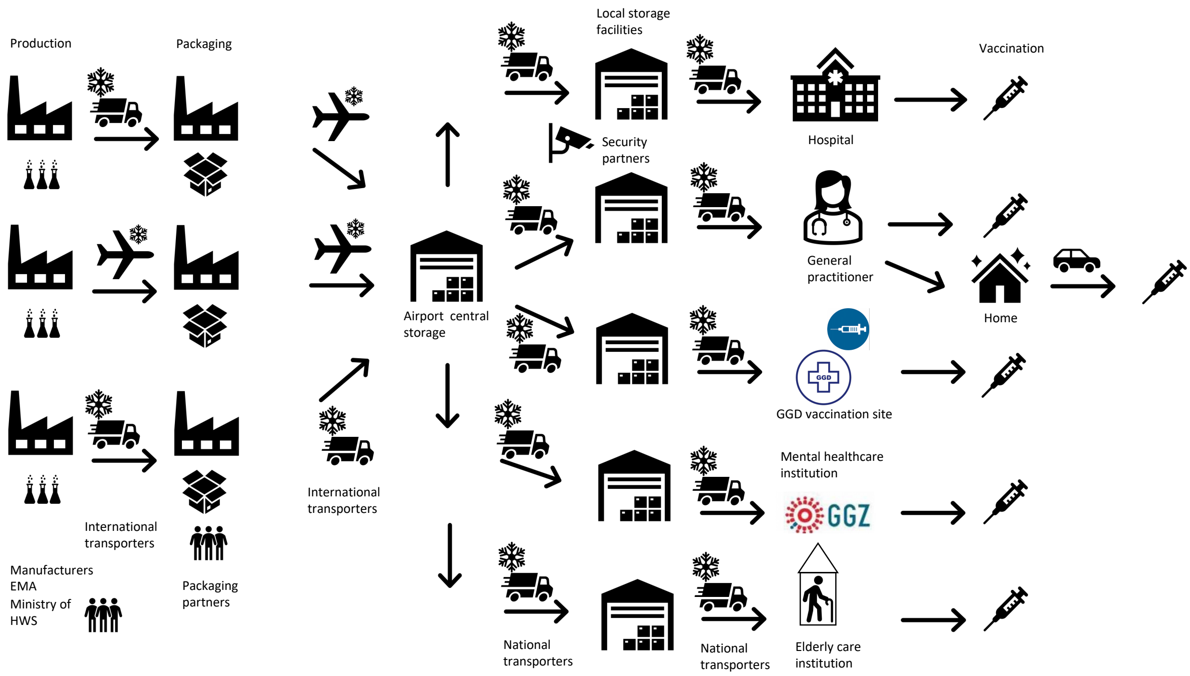


Figure 4: Overview of the complete vaccine supply chain

3.1.3 Actors

The actors involved in the system are presented in Figure 4 as well. The vaccine manufacturers, the European Medicine Agency (EMA) and the ministry of Health, Welfare and Sport are interacting in the first column of the supply chain. The manufacturers are obviously responsible for the production, the EMA is responsible for approval of vaccines to the European market and the Ministry of HWS makes the decisions regarding orders for different vaccines. Packaging partners are responsible for filling the vials and packing the vials in batches. When this final production step is finished, the vaccines are transported to the country of destination. From the central distribution center at the airport, the vaccines are distributed across the country and they will first be stored in local decentral storage facilities. These facilities cooperate with security partners to prevent damage on the vaccines or theft. From the decentral storages, the vaccine packages are transported to each of the vaccination sites, where actual inoculation will take place. All the refrigerated transports between de production, storage and unbundling locations to the vaccination sites will be carried out by both national and international transport partners.

This context description gives an overview of the bigger system wherein the focus of this research exists. The model boundaries are set to the vaccinations at general practices in a neighborhood, so home vaccinations are excluded.

3.2 Environment

A real existing neighborhood was chosen to model, in order to represent a realistic situation. The selected neighborhood is Oude Westen in Rotterdam, the Netherlands. Oude Westen is a located in the city center of Rotterdam. The neighborhood has about 9500 inhabitants. The composition of the population is diverse: singles, families with children and students live there. Residents and visitors describe Oude Westen as multicultural, diverse and lively (Gemeente Rotterdam, 2020). Since Oude Westen represents an average neighborhood in the Netherlands, it is not necessary to model the entire country. The results of experiments within the scope of Oude Westen can be generalized to the Netherlands. The location on the map is shown in Figure 5.

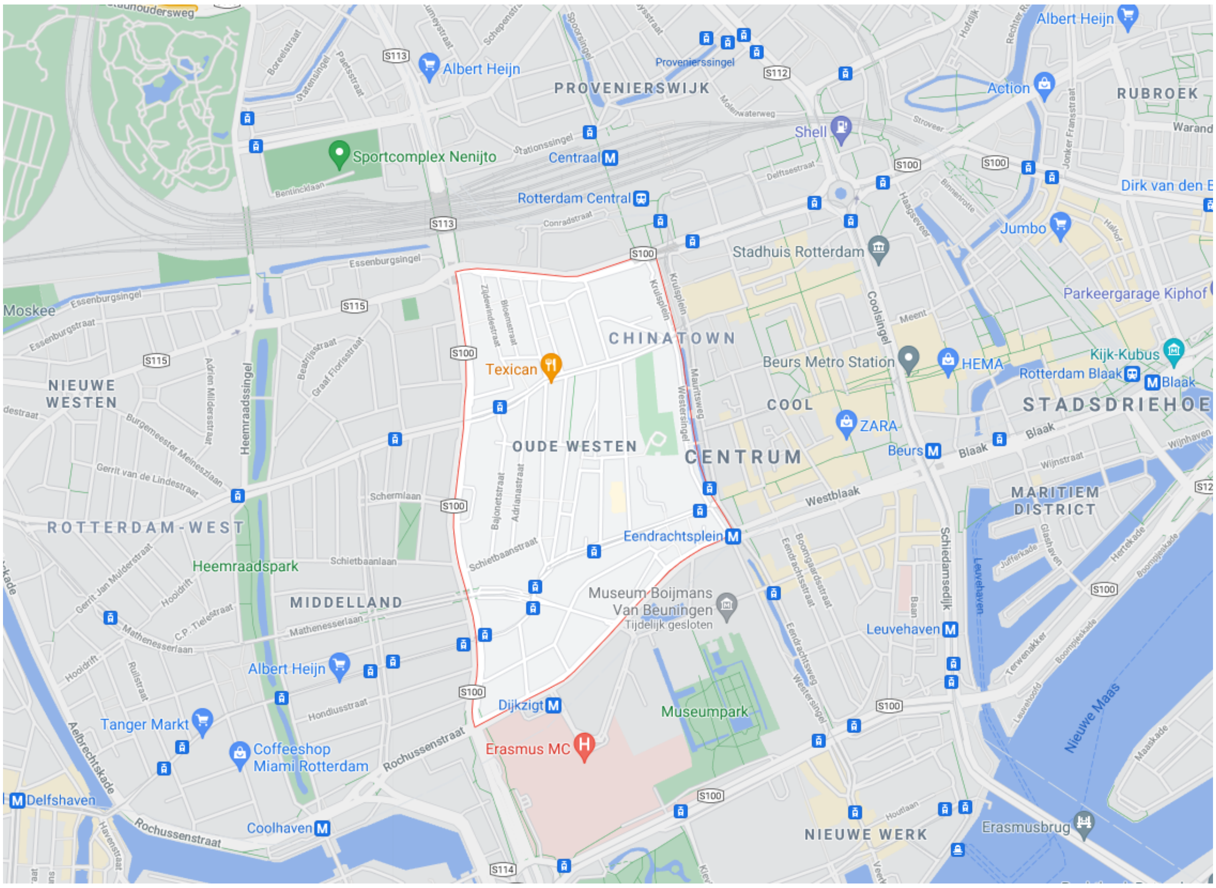


Figure 5: Location of Oude Westen

There are five general practices in Oude Westen (Google Maps, 2021). The GGD is located near metrostation Leuvehaven and the Erasmus hospital on the south side of Oude Westen. At the last national elections on march 17 2021, there were three voting locations in Oude Westen. The political party Forum voor Democratie (FvD) campaigned against the corona measures and vaccinations. This makes it plausible that a large part of their voters do not want to be vaccinated. However, the percentage of voters at polling stations in Oude Westen is not higher than in the whole of the Netherlands (Gemeente Rotterdam, 2021; Kiesraad, 2021). Therefore, it is assumed that there is no significant difference between the number of so-called anti-vaxxers in the Netherlands and in Oude Westen. Besides the doubters, 14% of the people will not take a vaccine (Mouter et al., 2020). There are 8370 inhabitants in Oude Westen, older than 15 years (Allecijfers.nl, 2021). In the model, these are the people that can receive a vaccine.

3.3 Modeling Approach

In order to answer the research questions, a simulation modeling approach is chosen to explore the design space. Simulation models are well-suited for evaluating dynamic decision rules under "what-if" scenarios (Min & Zhou, 2002). Simulation models were used by multiple researchers, like Wikner et al. (1991), Towill (1991) and Towill et al. (1992). They used these simulation techniques to evaluate the effects of various supply chain strategies on demand amplification (Beamon, 1998). System performance under uncertainty can be examined very well, because different scenarios are easy to implement in simulation models. The robustness of willingness to vaccinate can be tested by simulating various scenarios.

There are various simulation modeling approaches. In the field of logistics and supply chain management (LSCM), discrete-event simulation (DES) and system dynamics (SD) are two widely used modeling tools which underpin decision support systems (DSS) (Tako & Robinson, 2012). System dynamics models a system as a series of stocks and flows, in which the state changes are continuous. A system dynamics model views "entities" as a continuous quantity, flowing through a system of reservoirs connected by pipes. Discrete event simulation models systems as networks of queues and activities, where the state changes in the system occur at discrete points of time (Brailsford & Hilton, 2001). SD modeling is more often used at a strategic level and DES at a more operational/tactical level (Lane, 2000).
The Agent-based modeling (ABM) approach is often used for modeling system behavior, dependent on interactions between agents in de system. ABM allows the disaggregation of systems into individual components that can potentially have their own characteristics and rule sets (Crooks & Heppenstall, 2012). Since infections occur by interactions between agents in the system, ABM would be suitable for modeling the COVID-19 pandemic. A successful vaccination depends on the meeting and availability of agents in the system, namely the patient, the doctor and the vaccine. These availabilities depend on the outcomes of decision rules for each agent, but the input for these decision rules is uncertain. Thereby, willingness to vaccinate of people can be influenced by social contacts (Ni et al., 2021), so the development of willingness to vaccinate of the population is dependent on interactions between agents. With the insights provided by agent-based simulations, the answers on the research questions can be found. Therefore, an ABM approach is chosen to conduct this research.

The software used in this research is NetLogo. NetLogo is a multi-agent programming language and modeling environment for simulating natural and social phenomena Modelers can give instructions to thousands of independent agents that are all operating concurrently. This makes it possible to explore connections between micro-level behavior of individuals agents and macro level patterns that emerge from their interactions (Tisue & Wilensky, 2004). Therefore, this modeling software is suitable for investigating the developments of willingness to vaccinate and the epidemic by introducing different conditions of vaccine supply, social influence and service level.

In the next section, a schematic overview of the processes that will be incorporated in the model will be presented, using an IDEF0 scheme.

3.4 Conceptualization

In this section, the agents and model functions are conceptualized. The conceptual model represents the agent behavior and functions that should be translated into the simulation model. The agents and their behavior are conceptualized in section 3.4.1. The method that was used to conceptualize the processes of the system is IDEF0, which will be introduced in section 3.4.2.

3.4.1 Agents and behavior

In the table below the agents in the system are outlined. The features that they have are shown in the second column.

Table 3: Agents

Agents	What they have	What they do
Patients	Age Risk of hospitalization Risk of death Willingness to vaccinate A doctor Number of contacts per day Group of contacts Maximum number of contacts	Make an appointment Go to the doctor Getting vaccinated Influence other patients on willingness to vaccinate Consider whether getting vaccinated or not
Doctors	Injection capacity Vaccine inventory	Demand forecasting Order vaccines Call up patients Inject patient
Assistants	A doctor	Make appointments

3.4.1.1 Patients behavior

The behavior of patients is visualized in Figure 6. There are three main processes ongoing in the model:

- Vaccinations
- Social influence
- Spread of the virus

The process of getting vaccinated starts at the arrow at the top right. The processes of social influence and virus spread start by creating contacts at the arrow at the top left. The square boxes represent activities of the patients. The ellipses represent the state of the patients. Patients can end up in three states, namely vaccinated, not vaccinated or dead. Infected or hospitalized patients cannot start the vaccination procedure. They are allowed again to get vaccinated when they are recovered from their infection. The figure can be found on the next page.

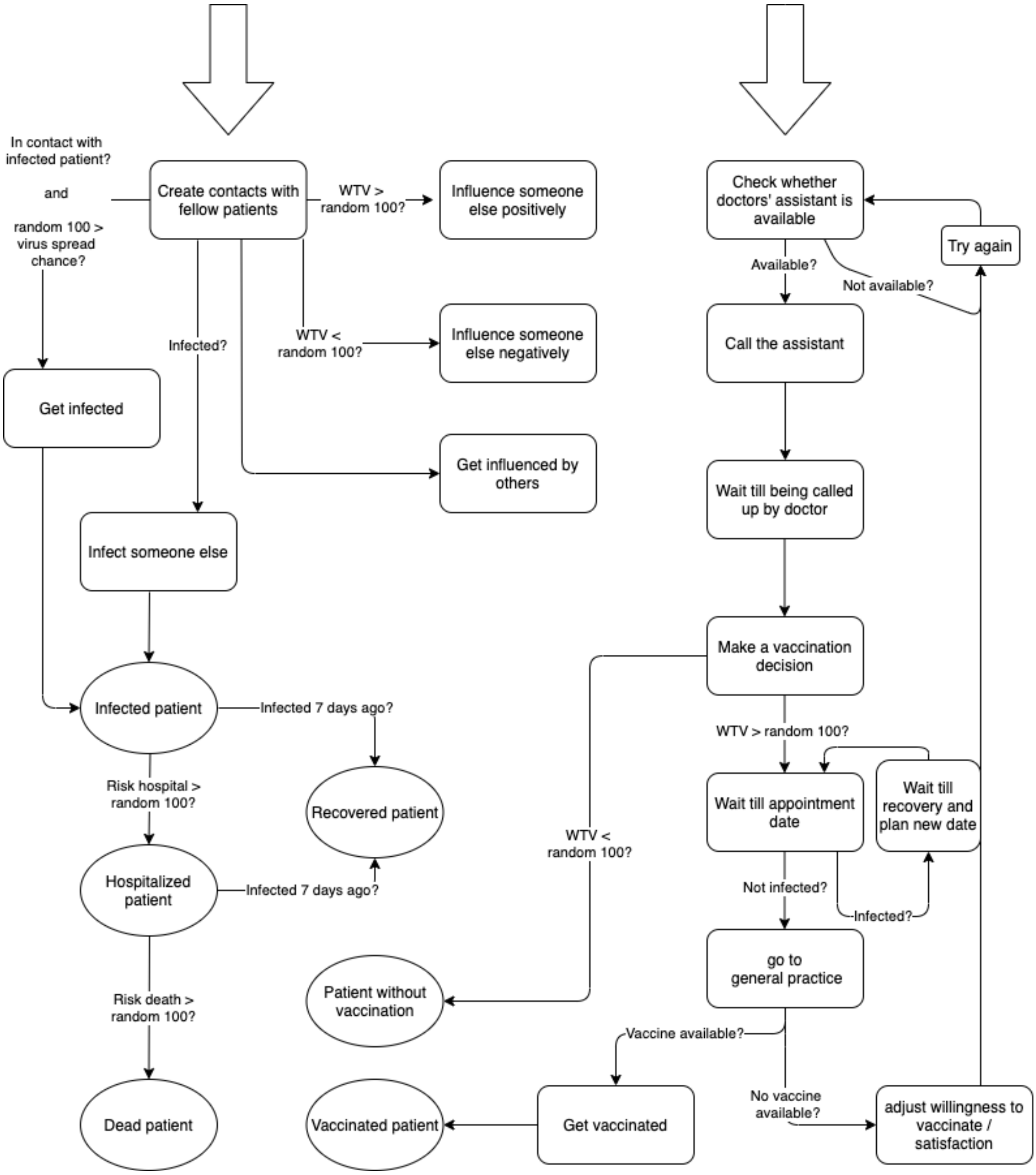


Figure 6: Patients behavior

The first main process is getting vaccinated. The vaccination order will be from old to young patients. The oldest patient makes an appointment with one of the assistants. After the patients have made their appointments, the doctor will call them up to come to the practice. At the moment of being called up, the patient makes a vaccination decision, based on its willingness to vaccinate (WTV). If it is the appointment date of a patient and the patient is not infected with the virus, the patient will go to the practice. If there is a vaccine available at the moment that the patient is at the practice, the patient will be vaccinated and will be immune to the virus.
The second main process is social influence and starts with creating contacts between patients. Patients have a maximum number of contacts per day, depending on their age. Older people have less contacts than younger people. Patients first try to make contacts within their own group of contacts. Depending on the individual willingness to vaccinate, a patient influences all of its contacts positively or negatively.

The other way around, the patient also gets influenced by its contacts and adjusts its willingness to vaccinate.
The third main process is the spread of the virus and occurs on basis of the same contacts as described for social influence. When a patient is in contact with an infected patient, the chance of getting infected is equal to the virus spread chance (and vice versa). Once infected, every patient has a chance of going to hospital or die, depending on age.

3.4.1.2 Doctors behavior

In Figure 7 below, the behavior of doctors is presented.

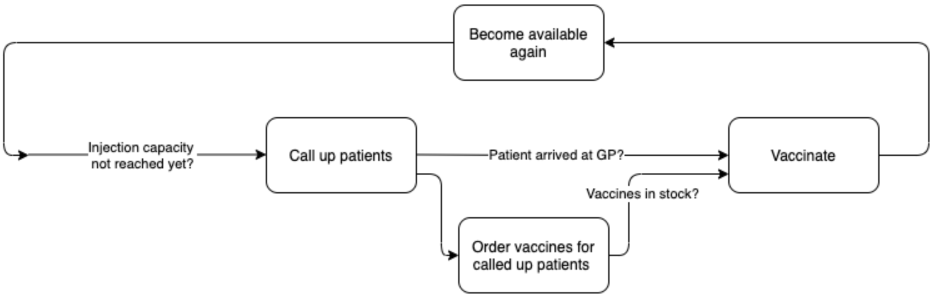


Figure 7: Doctors behavior

The doctor will call up the amount of patients, depending on his injection-capacity. The doctor also orders the number of vaccines needed. If there are no vaccines in stock for the doctor to order, he will not call up patients until there are new vaccines available. Just as mentioned in section 3.5.1.1, a patient will be vaccinated when a patient is present at the GP and a vaccine is available.

3.4.1.3 Assistants behavior

The behavior of assistants is simple. Their only task is to answer the phone when patients call to make an appointment. After a phone call, the appointment date is not set yet. This happens when a patient is called up by the doctors to come to the practice, but a patient must have called the assistant before he can be called up by the doctor. The behavior of the assistants is shown in Figure 8.

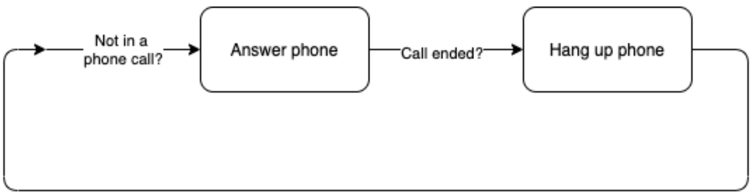


Figure 8: Assistants behavior

3.4.2 IDEF0 Scheme

IDEF0 is a methodology designed to model decisions, activities and actions within a process using a combination of graphics and text. The concept of IDEF0 is shown in Figure 9. The input is used, consumed or altered by the function. Controls are objects vital to produce an output, as they control the way the function is executed. Examples of controls are standards and regulations. Mechanisms support the execution of the functions. Triggers of processes are another type of controls. Examples of mechanisms are human resources and equipment (Lang et al., 2018). The IDEF-scheme gives insight in the needs and requirements, to successfully convert an input into a desired output.

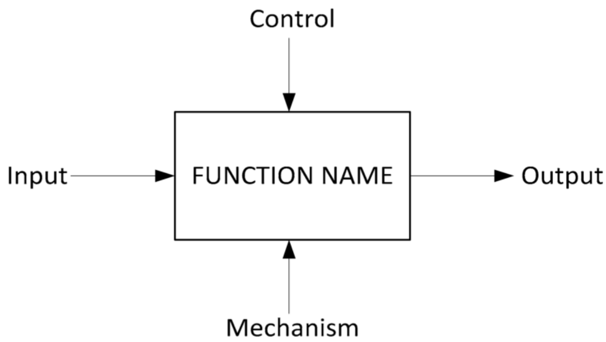


Figure 9: Concept of IDEF0

In the real world, there are three main processes for the distribution of vaccines:

- Vaccinations at the GP (or at home)
- Administrative process
- Supply, transport and storage

The detailed IDEF0 schemes of these processes can be found in Appendix A. Figure 107 on the next page is a conceptual representation of the processes that are incorporated in the model and thus the model demarcation. It is not exactly constructed according to the IDEF0 guidelines, but it links the relevant processes of different flows in one figure. An explanation of the IDEF0 scheme is provided on page 21.

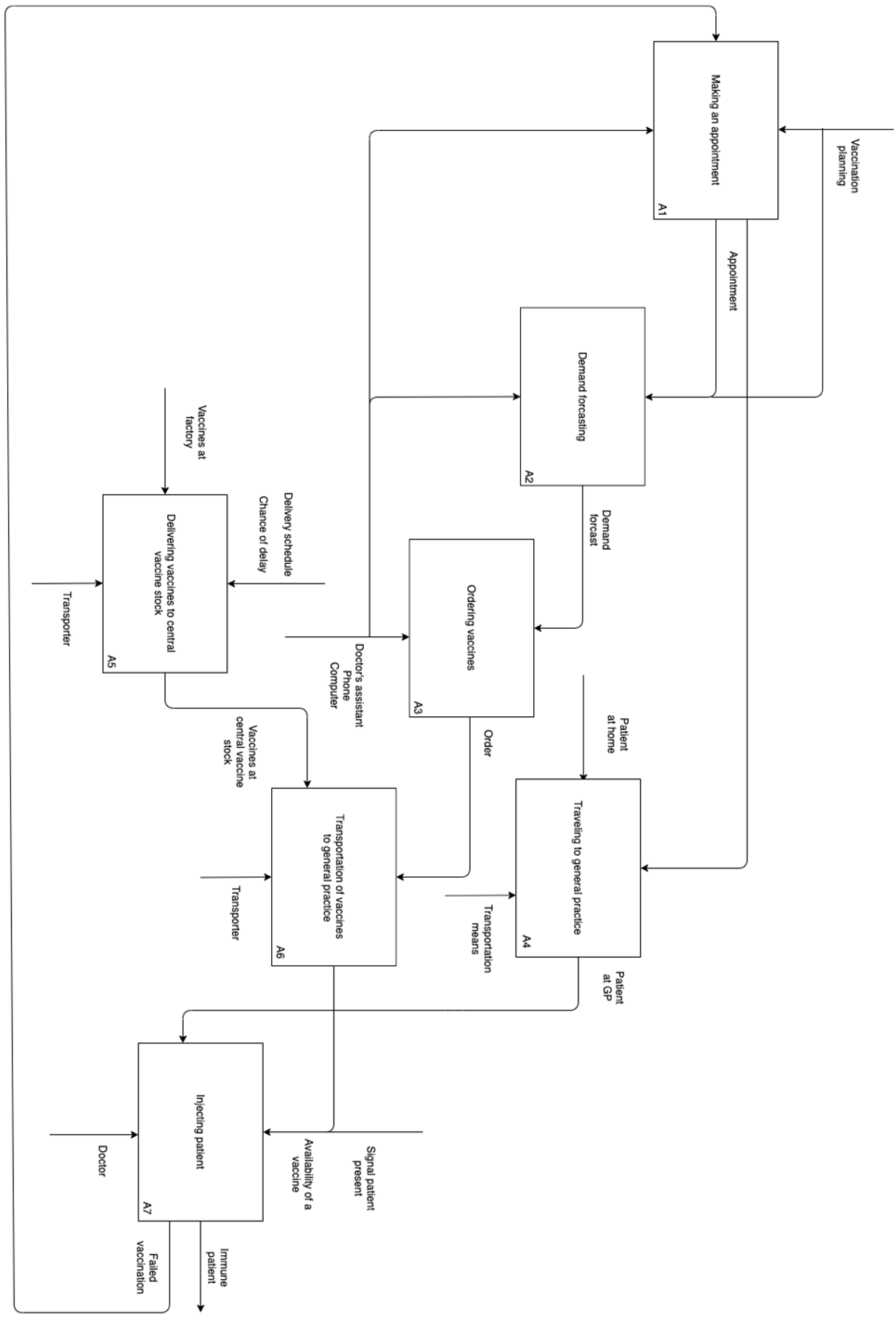


Figure 10: IDEF0 scheme vaccinations

The vaccination process starts with making an appointment and starts a flow of information. This sub-process is triggered when a it is a patients turn to make an appointment, according to the vaccination planning. The oldest patients are first allowed to make an appointment. Depending on the number of appointments, the doctor's assistant makes a demand forecast and orders the correct amount of vaccines. The outputs of the information flow are thus an appointment and an order.
An appointment is the trigger for a patient to start traveling to the general practice and an order is the trigger for starting to transport the vaccines from a central vaccine stock to the general practice. The patient can be injected when he is present at the general practice, as well as a vaccine that is available. In case that there are not any vaccines in stock at the general practice, the patient cannot be vaccinated and has to go through the entire process again.
The last process that needs some clarification is the delivery of vaccines at the central vaccine stock. According to the delivery planning, fixed amounts of vaccines should be delivered at the end of every week. This is external process from the vaccinations and does not depend on the planning of appointments and orders. However, the vaccinations do depend on the vaccine restocks, because vaccines must be available when vaccinating a patient. There is a chance of delay, which possibly results in a shortage of vaccines and cancelations of appointments.

In this section, the processes incorporated in the model have been outlined. The translation of the conceptual model into a simulation model will be explained in section 3.5.

3.5 Specification

In this section, the translation from the conceptual model into a simulation model is presented. First, the model parameters and KPIs are explained in section 3.5.1. Thereafter, the data that is used in the model is presented in section 3.5.2, followed by a list of modeling assumptions that needed to be made to generate an approach to reality in the model in section 3.5.3. The exact translation of the conceptual model can be found in the code of the simulation model. The model is attached in the TU Delft repository.

3.5.1 Explanation of parameters and KPIs

Some of the parameters and KPIs in the model need some explanation to understand the results. In this section, it will be explained how these parameters and KPIs are constructed in the model and how the concepts interact with each other. The full list of parameters and KPIs can be found in Appendix B.

3.5.1.1 Parameters

There are four parameters that influence willingness to vaccinate, namely influence service, social influence, delivery time and probability delay.

Influence service represents the number of percentage points that willingness to vaccinate / satisfaction will decrease after a failed vaccination. For example; if this value is set to 10, a patients willingness to vaccinate will decrease from 90 to 80 in case of a failed vaccination / cancelation of appointment.

Social influence is the number of percentage points that the willingness to vaccinate of a patient increases or decreases when it is being influenced. Every day, each patient creates a couple of contacts with other patients. A patients' willingness to vaccinate is the chance of positively influencing its contacts and 1 – willingness to vaccinate is the chance of negatively influencing its contacts.

Delivery time is the time from ordering vaccines from the central vaccine stock to delivery at the general practice. This parameter is also used to determine the appointment date of a patient. The waiting time between making an appointment and the appointment date is equal to the delivery time. Each day of waiting time influences willingness to vaccinate.

3.5.1.2 KPIs

There are a couple of important KPIs that are not straightforward. Vaccination rate, willingness to vaccinate / satisfaction and failed vaccinations are explained below.

Vaccination rate is number of patients that took the vaccine, divided by the total number of patients. A patients' willingness to vaccinate at the moment that a patient makes an appointment for the first time is the chance of getting a vaccine.

Willingness to vaccinate and satisfaction are captured in the same variable, because the service level (i.e. waiting times, number of failed vaccinations) and social influence determine the willingness to vaccinate. The vaccination decision is made at the first time that a patient makes an appointment (see section 3.5.3), but willingness to vaccinate is not influenced by the service level at this moment, because the waiting time starts at this moment and a failed vaccination cannot occur before making the first appointment. At the moment of actually vaccinating, service level had an effect on willingness to vaccinate in the form of satisfaction. Willingness to vaccinate / satisfaction at the moment of vaccination is the chance of getting vaccinated, if the decision would be made at the moment of vaccination, after service level played a role in making the vaccination decision.

Failed vaccinations is the number of vaccinations that did not take place because of unavailability of vaccines when the patient came to the general practice for its vaccination. A failed vaccination represents a canceled appointment. A failed vaccination influences willingness to vaccinate / satisfaction by the value of parameter ‘influence service’.

In this section, the meaning, constructions and interactions of parameters and KPIs in the model were explained. In section 3.5.2, the data that was used in the model will be discussed.

3.5.2 Data use

In this section, the data that was used in the model will be discussed. In order to realize an approach to reality, a couple of real world data sources were used in the code of the model. The types of information and their reference are outlined in Table 4 below.

Table 4: Data references

Information	Reference
Willingness to vaccinate by age	RIVM (2021). Bereidheid om te laten vaccineren. https://www.rivm.nl/gedragsonderzoek/maatregelen-welbevinden/vaccinatiebereidheid
Risk of hospitalization and death by age	The Economist Group. (2021) See how age and illnesses change the risk of dying from covid-19. The Economist. https://www.economist.com/graphic-detail/covid-pandemic-mortality-risk-estimator
Mean time of hospitalization	RIVM. (2020). *Het nieuwe coronavirus in Nederland. Wat is het verschil tussen de eerste golf en de tweede golf?* https://www.rivm.nl/sites/default/files/2020-10/EersteGolf_vs_TweedeGolf.pdf
Injection capacity of doctors	Ritter, F (2021). Personal interview.

The RIVM (2021) did 12 rounds of surveys among the Dutch population about their willingness to vaccinate. They provide an overview of people's attitude to vaccination and their reasons to get vaccinated or not. They also include information about people's information sources where their opinions are based on. The Economist (2021) published a tool to estimate the risk of hospitalization and death caused by COVID-19 for any age. They also give insights in additional risk caused by underlying medical conditions like asthma or obesity. In a personal interview with Fränk Ritter, general practitioner in Rotterdam, he shared his successful approach to vaccinating his patients. His strategy turned out to be very successful, as a result of putting a lot of afford in providing his patients with personal information. The number of patients that he could vaccinate came down to 4 per hour. This value will be used to calculate the share of time that a doctor would spend on vaccinating, given the injection capacity used in the model runs.

Not all information is captured by data. Therefore, a couple of modeling assumptions were made to generate an approach to reality. These assumptions will be outlined in the next section.

3.5.3 Modeling assumptions

In this section, the assumptions made for modeling the vaccination system are outlined. Since not all real world information is captured in data sets, making assumptions during the modeling process is inevitable. Sometimes, when information is actually captured by data, still an assumption has to be made to translate the information to the model. Besides the availability of information, it is impossible to take all aspects of the real world into account. Therefore, some simplifications have been made. The assumptions and simplifications made in this simulation model are listed below.

- An infection or hospitalization takes seven days (RIVM, 2020). After infection, a patient is protected to the virus for 8 weeks.
- There is no incubation time of the infection.
- Patients are not going in quarantine after an infection.
- Younger people have more contacts per day than older people.
- Patient just need 1 injection to become immune, considering the fact that vaccinations in next year will not be the first injection for most people.

- Patients have one moment per day to infect each other, go to hospital or die.
- Doctors will only call up their patients if there are vaccines in stock.
- On the first moment that a patient is able to make an appointment, the patient decides whether he will get vaccinated. This decision does not change anymore.
- If the delivery time of vaccines is 48 hours, a patient will make an appointment for 48 hours in the future. A safety waiting time can be added or subtracted from the appointment.
- The willingness to vaccinate of patients is influenced by social contacts, the waiting time between making an appointment and vaccination, and the eventual cancellation of appointments due to insufficient vaccine stocks.
- As long as the amount of patients to be vaccinated is larger than the injection capacity, the order size of the doctors is determined by the delivery time and their injection capacity. If the delivery time is 48 hours, they will order the amount of vaccines that they can inject in 48 hours. The order moment is immediately after the delivery of vaccines.
- Vaccines are restocked at the central vaccine stock at the end of every week. This is a fixed amount of vaccines, that equals the injection capacity of the doctors. There is a chance of delay. The duration of the delay is random with a maximum of four weeks.
- Hospitalization of a contact within a patients group causes an increase of 5% of willingness to vaccinate. Death of a contact results in 15% additional increase of willingness to vaccinate.
- The virus spread chance is 15%
- Only doubters are influenced by social contacts. People who already know if they are getting a vaccine at the setup are not influenced on their attitude. However, when someone in their group of contacts goes to hospital or dies, their willingness to vaccinate increases and they become doubters.
- The utilization of vaccines is 100%. There are no vaccines being wasted.

This section provided insight in the translation from the conceptual model into an agent-based simulation model. The discussed topics are parameters and KPIs, data use and modeling assumptions. In section 3.6, an overview of the model interface in Netlogo will be presented.

3.6 Model interface

In Figure 11, an overview of the model interface is presented. Each slider in the interface represents a parameter and can be adjusted easily. The monitors on the right side show the current values of the KPIs (see section 3.5.2.2). According to the number of doctors in Oude Westen, there are five doctors visible in the model. Doctors / General practices are indicated by a green house. The red people at the general practices represent the doctors' assistants. The rest of the agents in the system are patients. Initially, patients are black. When they made an appointment with the assistant, they turn pink. When patients are called up, they create a link with the doctors and turn black again. Red patients are infected with the virus.

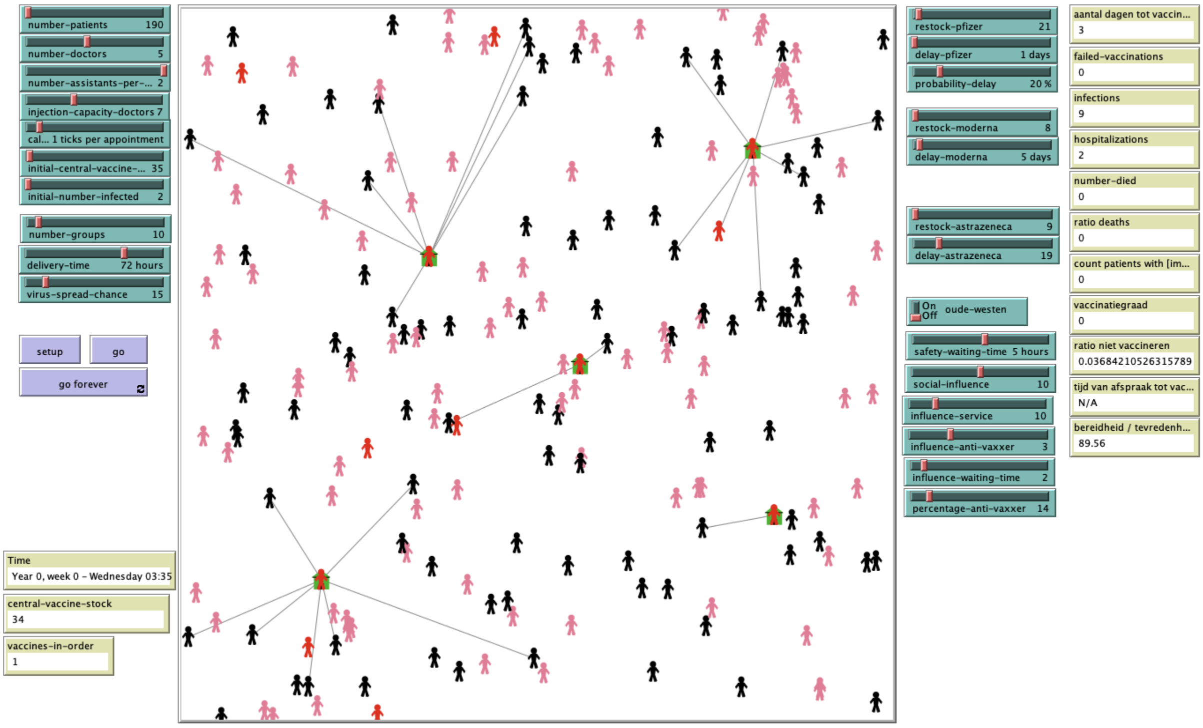


Figure 11: Model interface in NetLogo

In the next section, the outcomes of the verification experiments will be discussed.

3.7 Model Verification

In this section, the model verification will be discussed briefly.

The model is verified by executing a couple of experiments, in order to check whether the model functions work as intended. Model verification deals with building the model right (Balci, 1998). When a simulation language is used, verification is primarily concerned with ensuring that the model has been programmed correctly in the simulation language. The primary techniques used to determine that the model has been programmed correctly are structured walkthroughs and traces (Sargent, 2013). This has been widely done during the debugging of the model. Debugging identifies errors causing the model to fail and changes the model accordingly in order to correct these errors (Roungas et al., 2018). In addition, a couple of situations were set up for the model verification, with a low amount of patients, so that their functioning can easily be checked manually.

In three verification experiments, it has been tested whether patients create contacts every day as intended, whether the doctors use their full capacity every day and whether the social influence mechanism works properly. These functions turned out to be working well. The full explanation of the verification experiments and results can be found in Appendix C.

3.8 Model Validation

Model validation deals with building the right model. Model validation substantiates that the model behaves with satisfactory accuracy, so that the approach of reality is sufficient, within the domain of applicability of the model.

3.8.1 Comparison of parameter effects to expectations from the real system

For the first validation experiment, the face validity of the model have been examined. To test the face validity, it is tested if there exist a reasonable fit between the feedback structure of the model and the essential characteristics of the real system (Martis, 2006). It has been checked whether an increase or decrease of some model parameters cause the expected effect on model outputs, based on system behavior developments in the real world. The technique of Assertion Checking checks if something is happening opposed to what the modeler assumes that should happen, thus detecting potential errors in the model (Balci, 1998).
Most of the changes in parameter settings caused the expected effect. For the effects that could not be explained by functions in the model, some adjustments were made in the code. The experimental setup, results, explanations of unexpected behavior and the adjustments are presented in Appendix D.

3.8.2 Comparison of vaccination rate dynamics to the real system

In the second validation experiment, the development of the vaccination rate was analyzed. For this experiment, the willingness to vaccinate in the Netherlands in January 2021 was used as initial value. This value was around 75% in January and increased to 90% in May (RIVM, 2021). Besides the time frame in which this happened, the model shows the same behavior. In reality, this development took five months and in the model just five weeks. This difference is caused by a different number of patients and the constant efficient vaccination speed in the model, whereas the vaccination campaign in the real world started very slow and speeded up over time. Nevertheless, the model can be considered as valid for the purpose of this research, since it is able to show behavior similar to the real world.

On basis the different experiments with the model parameters, analysis of the model outcomes and after revising some parts in the code, the conclusion can be drawn that the model shows behavior as we expect from the real world system and the accuracy of the behavior is sufficient within the domain of applicability of the model. In the next chapter, the experimental setup will be outlined.

4. Experimental setup

In this chapter, the setups of the different experiments will be outlined. Before experimenting with the different parameters, a test with a scaled model with less agents have been done, in order to reduce the required running time of the model. According to the research questions a couple of parameters have been varied to examine the impacts on the KPIs.

4.1 Scaled model

A couple of runs have been done to compare the scaled model with the real sized model. In section 4.1.1, the parameter setup for both models is outlined.

4.1.1 Parameter setup

First, the model will be run with 8370 patients, according to the number of inhabitants in Oude Westen, to explore the outcomes. The probability of delay was varied from 0% to 100% with intervals of 20. Because of the long running time, each variation of input was run just once. The input settings can be found in Appendix E.
The output of the model settings was compared to the model output of some runs with 1/6 of the number of patients. For these runs, the availability of vaccines and injection capacity of the doctors were scaled down with the same factor. The adjusted setup can be found in Appendix E.

4.1.2 Comparison of model outcomes

In this section, the outcomes of the scaled model and real sized model will be compared. As outlined in section 4.1.1 the probability of delay was increased from 0% to 100%, in order to compare the behavior of the scaled model with the behavior of the real sized model. The effects on the time to complete all vaccinations, the vaccination rate and satisfaction are presented in the figures below.

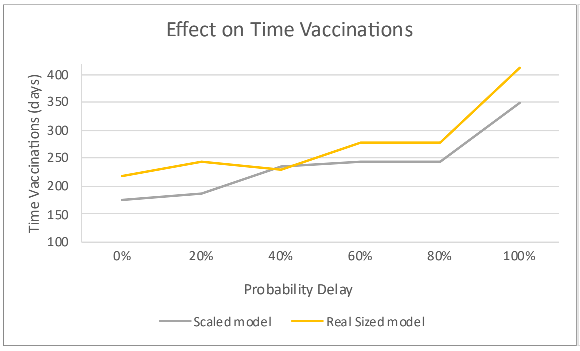


Figure 12: Effect of probability delay on time vaccinations

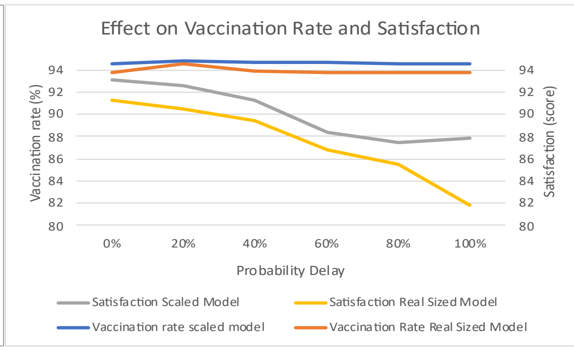


Figure 13: Effect of probability delay on vaccination rate and satisfaction

The real sized and the scaled model show similar behavior. Although not all values are the same, the increase of the probability of delay has similar effects on the outputs of both models.

In order to get more reliable insights in the similarity of the models, another couple of runs were done in order to further test the similarity of both models. Since random numbers play a significant role in these simulations, extra replications can provide us information on how to interpret the outcomes of the scaled model to draw conclusions about the real world. For these extra runs, the scenario of 20% chance of delay was used.

Table 5: Setup for model comparison

Model	Number patients	Probability-delay	Replications
Real size	8370	20%	8
Scaled	1395	20%	10

The outcomes are presented in Table 6. For each value, the 95% confidence is calculated as well. When the 95% confidence interval is small, relative to the KPI value, an outcome in the scaled model can be adjusted to the value in the real sized model. The usability of the outcomes will be discussed below the table.

Table 6: Outcomes of test runs

KPI	Scaled model	95% confidence interval	Real sized model	95% confidence interval
Time vaccinations	201	6	249	10
vaccination rate	0,94	0,00	0,94	0,00
ratio death	0,00	0,00	0,00	0,00
infections	78	31	137	43
hospitalizations	23	9	42	12
failed vaccinations	110	29	1029	115
mean time from first appointment to vaccination	129,20	31,62	226,13	30,76
Willingness to vaccinate / satisfaction	91,25	0,64	89,20	0,54

- The values for vaccination rate, ratio death and willingness to vaccinate / satisfaction are similar in both models and both have small 95% confidence intervals, so these values don't need to be adjusted.
- Time vaccinations in the real sized model is about 20% longer than in the scaled model. The 95% confidence intervals are small, relative to the values, so it is assumed that time vaccinations is approximately 20% longer in the real sized model.
- Failed vaccinations and mean time from first appointment to vaccination have different values and quite large 95% confidence intervals. The difference is explainable, because delays in the real sized model relate to bigger orders that are delayed, which result in more canceled appointments. In the same way, more cancellations lead to longer waiting times until the vaccination is done. Because of the large 95% confidence intervals, the values will not be converted by multiplying is with a certain value, but the difference was kept in mind when drawing conclusions.
- No conclusion can be drawn about the comparability of the values for infections and hospitalizations. The very large 95% confidence intervals indicate that infections are strongly dependent on random numbers. The model behavior regarding infections will be analyzed in chapter 5, but no hard conclusions will be drawn about the real world situation.

4.2 Experiments

In this section, the experimental setup is outlined. The reference parameter setting can be found in Appendix E.

4.2.1 Experiment 1: Impact of probability delay (RQ 1)

In order to answer research question 1, six scenarios are run with a different probability of delay, to investigate the impact of uncertainty of deliveries on the time that it takes to vaccinate the population and the vaccination rate. The probability was varied from 0% to 40% with an interval of 10%. Running these scenarios also gives insights in the impact on the number of infections, hospitalizations, service level (i.e. the time from first appointment to vaccination and the number of failed vaccinations).

Table 7: Setup experiment 1

Parameter	Variations	Replications
Probability delay	0% - 10% - 20% - 30% - 40%	10
Model	With positive and negative social influence	

4.2.2 Experiment 2: Impact of social influence (RQ 2)

The following experiment was set up to answer research question 2. The initial willingness to vaccinate of the population is around 90%. In the model, that means that the chance that a patient influences another patient in a positive way is very high. The parameter 'social influence' can work in either a positive or a negative direction, so when the value of social influence is being increased, it has a marginal effect on the willingness to vaccinate (see section 5.1). Therefore, the model was adjusted in a way that social influence only has a negative effect on the willingness to vaccinate and therefore the vaccination rate. The parameter of social influence was varied from 0 to 10 with an interval of 2.

Table 8: Setup experiment 2

Parameter	Variations	Replications
Social influence	0 – 2 – 4 – 6 – 8 – 10	10
Model	Without positive social influence	

4.2.3 Experiment 3: Increased social influence in combination with 20% delay (RQ 1 and 2)

From experiment 2, it can be concluded that the effect of negative social influence on the vaccination rate is limited. Therefore the increased social influence was combined with 20% probability of delay. In that scenario, patients have more time to influence each other before making a decision to get vaccinated or not. That will possibly lead to a lower vaccination rate.

Table 9: Setup experiment 3

Parameter	Variations	Replications
Social influence	0 – 2 – 4 – 6 – 8 – 10	10
Probability delay	20%	
Model	Without positive social influence	

4.2.4 Experiment 4: Low and high service levels (RQ 3 and 5)

In order to investigate the relation between the service level of the system and the vaccination rate, the service level was not only lowered to test the impact on the vaccination rate, but also increased to a very high level, so that the vaccinations will go very quickly. With such scenarios, it could be evaluated if a high pace of vaccinating can cause an increase of vaccination rate. In order to increase the service level, the vaccine supply, injection capacities were increased and the delivery time was decreased, so that patients have a very short waiting time. The input values of the experiments with a low service level are shown in the Table 10 below.

Table 10: Setup experiment 4: low service levels

Parameter	Variations	Replications
Delivery time	24 – 36 – 48 – 72	10
Injection capacity	1 – 2	
Restock Pfizer	21 – 41	
Restock Moderna	8 – 17	
Restock AstraZeneca	9 – 17	
Initial central vaccine stock	35 – 70	
Model	Without positive social influence	

The values in Table 11 below are used for the experiments with a high service level.

Table 11: Setup experiment 4: high service levels

Parameter	Variations	Replications
Delivery time	1	10
Injection capacity	2 – 4 – 6 – 8 – 10	
Restock Pfizer	100	
Restock Moderna	100	
Restock AstraZeneca	100	
Initial central vaccine stock	1400	
Model	With positive and negative social influence	

4.2.5 Experiment 5: Tipping point vaccination rate (RQ 4 and 5)

For the last experiment, the values of service level, negative social influence and uncertain deliveries will be pushed, until a tipping point is reached that the vaccination rate decreases to a value below the threshold of immunized people to achieve herd immunity. According to (Lippi & Henry, 2021), this threshold is around 70% of the population.

Table 12: Setup experiment 5

Parameter	Variations	Replications
Delivery time	24 – 36 – 48 – 72	10
Social influence	4 – 6 – 8 – 10	
Probability delay	20% – 40%	
Model	Without positive social influence	

In this chapter, the experimental setups were outlined. Because of an extremely long running time of the real sized model, a scaled model with 1/6 of the number of patients, injection capacity and vaccine supply was introduced. The scaled model does not generate the same outcomes for all variables, but the scaled model was considered usable with eventual adjustments of interpretation of the outcomes. In the next chapter, the results of the experiments outlined in this chapter will be analyzed.

5. Analysis of results

In this chapter, the results of the experiments described in chapter 4 will be presented and analyzed. The results will be discussed in the same order as the experiments presented in section 4.2.

5.1 Effects of increased probability of delay (RQ 1)

For this experiment, the probability of a delay of delivery to the central vaccine stock was varied from 0% to 40%. The impact on the vaccination time is shown in Figure 14. The graph also shows the 95% confidence interval of the mean of every scenario.

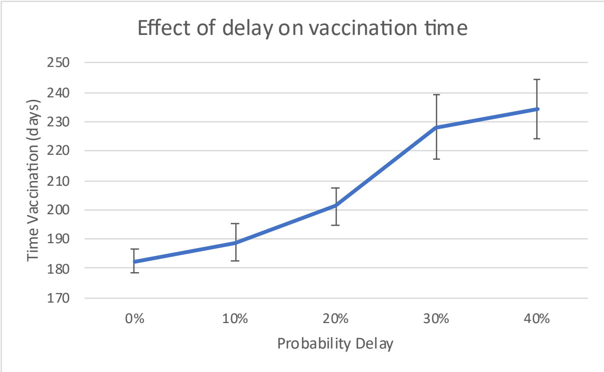
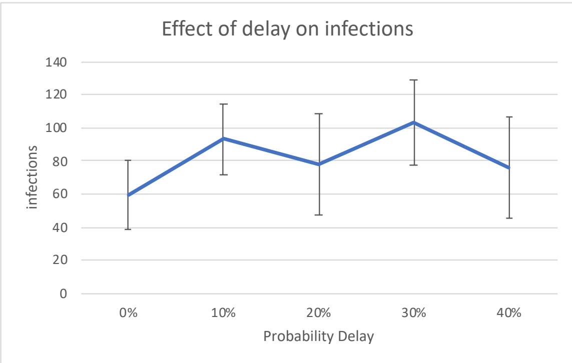


Figure 14: Effect of delay on vaccination time

When there are no delays introduced, the vaccinations take 182 days. By increasing the chance of delay, the time to vaccinate all people in the neighborhood that are willing to vaccinate increased up to 234 days. The question is whether this is a problem. That depends on the development of the number of additional infections are caused as a result of the longer vaccination time and the effect on the vaccination rate. The effects on these KPIs are shown in the graphs below.



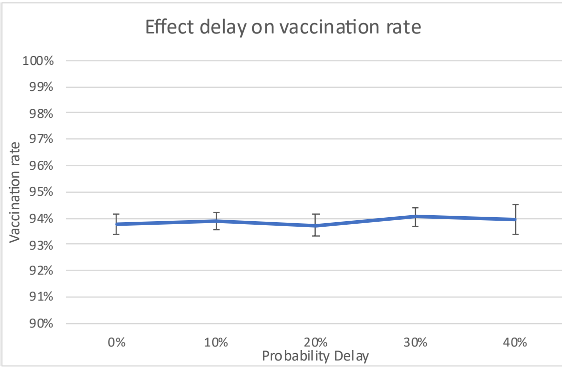


Figure 15: Effect of delay on infections

Figure 16: Effect of delay on vaccination rate

From Figure 15, it can be concluded that the number of infections is strongly dependent on random values. This can be derived from the very large error bars in the graph, which represent the 95% confidence interval. The effect of delay does not have any effect on the vaccination rate. This means that the increased waiting time does not discourage patients enough to let them make the decision to not take the vaccination, within the time from the start of the simulation till the moment of their first appointment. Eventual failed vaccinations don't have an effect on the vaccination rate, because the vaccination decision is made at the first appointment and does not change anymore. However, the willingness to vaccinate variable, where this decision is based on, keeps changing until the moment that a patient actually gets a vaccine. The final value of willingness to vaccinate is called "satisfaction" and is determined by social influence, waiting time and failed vaccinations. The development of satisfaction and failed vaccinations are shown in Figure 17 and Figure 178.

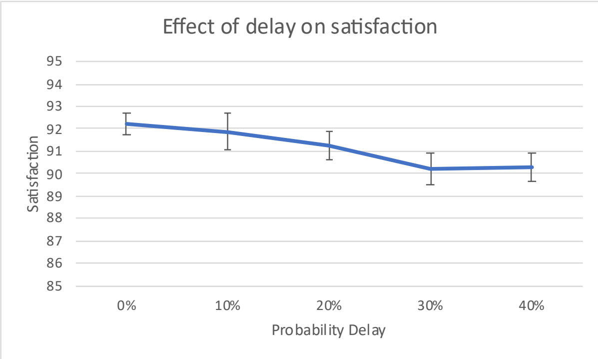


Figure 17: Effect of delay on satisfaction

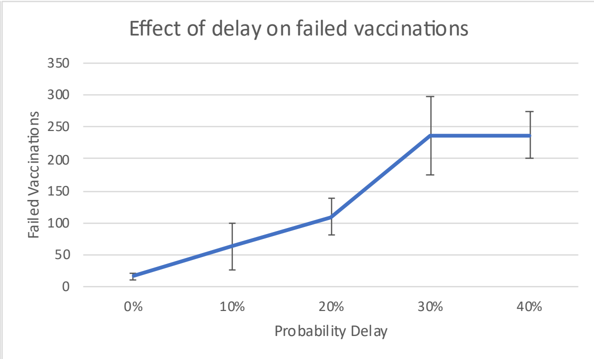


Figure 18: Effect of delay on failed vaccinations

The introduced delays have an effect on satisfaction, but it is still limited. When we compare the graphs of satisfaction and failed vaccinations, it can be concluded that the effects on satisfaction are mainly caused by the increase of failed vaccinations. That can be derived from the slope becoming horizontal in both graphs between 30% and 40% chance of delay.

From this experiment, the conclusions can be drawn that the introduction of 40% chance of delay causes approximately 30% extra time to vaccinate the patients in the scaled model. Note that the actual values of vaccination time would be around 20% higher in the neighborhood. The vaccination rate does not decrease, because failed vaccinations don't have any impact on the vaccination decision. However, delays in delivery cause an increase in failed vaccinations and therefore, the satisfaction of patients decreases. Satisfaction is a good indicator for the vaccination rate, if the vaccination decision would be made at the moment of actual vaccination. However, the effect of delays on satisfaction in this simulation is limited. For the real world, satisfaction would be a bit less, since more failed vaccinations would occur in a simulation with more patients.

5.2 Effects of negative social influence (RQ 2)

For experiment 2, the model was adjusted in a way that only negative social influence has an effect on willingness to vaccinate / satisfaction (see section 4.2.2). The social influence was increased from 0 percentage points to 10 percentage points. Just like in experiment 1, the vaccination rate did not change by increasing the parameter. Therefore, only the impact on satisfaction is presented in Figure 19.

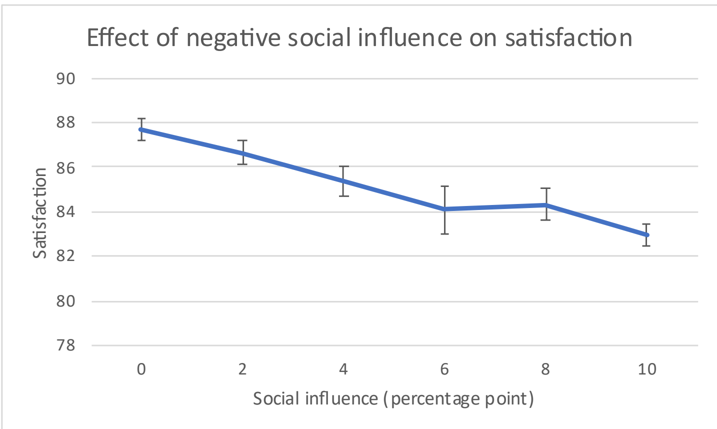


Figure 19: Effect of negative social influence on satisfaction

From the graph, we can conclude that negative social influence has an effect on satisfaction / willingness to vaccinate. When social influence is increased from 0 to 10 percentage points, satisfaction decreases from 87.7 to 83.0. This indicates that the vaccination rate would have decreased to 83%, if the vaccination decision had been made at the moment of actual vaccination. This decrease can be considered very little, because a social influence of 10 percentage points is a lot. It corresponds to a decrease of 10 percentage points of willingness to vaccinate, every time that a patient has contact with someone with a negative attitude towards vaccination. The initial willingness to vaccinate is quite high. Therefore, the chance of a patient influencing someone negatively is low and an increase of the parameter "social influence" does not enlarge that chance. It only causes a bigger effect when it happens. This is the reason why the effect is limited.

The effect of increased negative social influence on infections is shown in Figure 20.

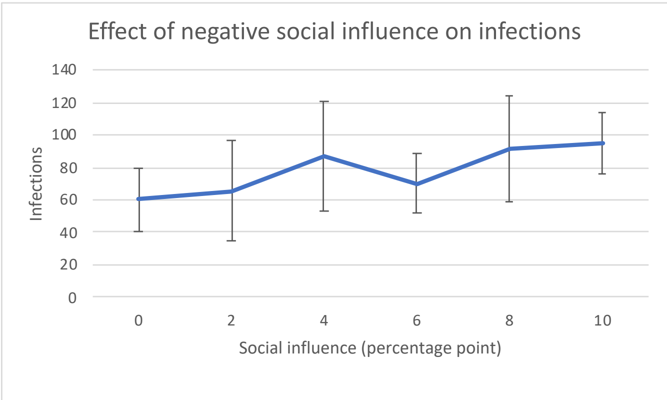


Figure 20: Effect of negative social influence on infections

In this experiment, increased negative social influence seems to have an effect on the infections. Nevertheless, this conclusion cannot be drawn, because of large error bars in the graph, that represent the 95% confidence interval. In addition, the vaccination time and vaccination rate, which could have an effect on infections, hardly changed. Therefore, the increase of infections cannot be explained and must be strongly dependent on random numbers.

From experiment 2, it can be concluded that negative social influence has a limited effect on satisfaction / willingness to vaccinate. For a value of 10 percentage points of negative social influence, satisfaction decreases with 4 percentage point in comparison to no negative social influence. We can generalize this result to the world, since negative social influence does not stimulate failed vaccinations or waiting time.

5.3 Effects of negative social influence in combination with 20% chance of delay (RQ 1 and 2)

From experiment 2, the effect of negative social influence on satisfaction turned out to be limited. Experiment 1 showed that introduction of delays has a limited effect on satisfaction, but this limited effect increases the chance that patients influence each other in a negative way. Therefore, the same setup as for experiment 2 was run, but with a 20% probability of delay. The results are shown in Figure 21.

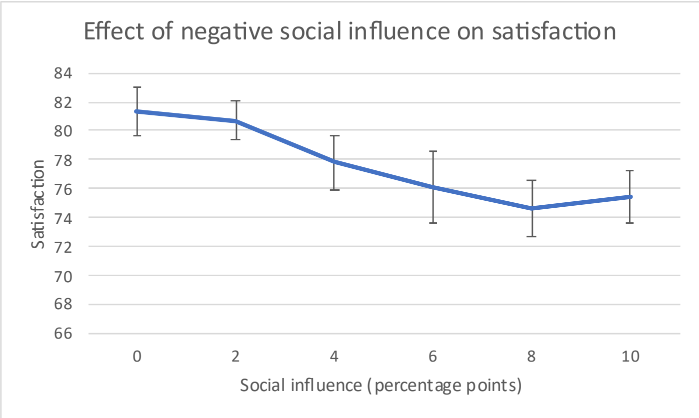


Figure 21: Effect of negative social influence on satisfaction

The graph shows a decrease in satisfaction when negative social influence is getting bigger. As expected, negative social influence has a greater impact when some delays are added to the simulation. A value of 8 percentage points for social influence decreases satisfaction with 6.7 percentage points in comparison with the scenario without negative social influence. This is still not a very big effect.
The slight increase of satisfaction between after an increase of social influence from 8 to 10 is caused by a shorter mean waiting time and less failed vaccinations.
The effect of negative social influence on infections is shown in Figure 22.

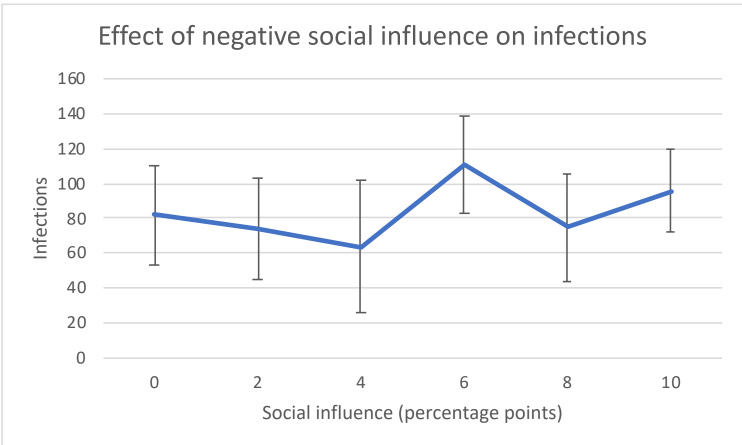


Figure 22: Effect of negative social influence on infections

In line with the previous experiments, the infections turn out to be strongly dependent on random numbers, since the graph does not show a trend and the 95% confidence intervals are very large.

From this experiment, the conclusion can be drawn that adding delays causes a larger impact of negative social influence, but still limited. Actual values for satisfaction will be a bit lower in the real world, because of additional failed vaccinations caused by the delays.

5.4 Effects of low and high service levels (RQ 3 and 5)

In this section the results of the experiments with low and high service levels will be discussed.

5.4.1 Low service levels

For this experiment, the delivery time was increased for both a setting with half injection capacity and vaccine supply as well as for a setting with the reference injection capacity and vaccine supply. The probability of delay was set to 20%. The effect of increased delivery times on the time to vaccinate the population is shown in Figure 23.

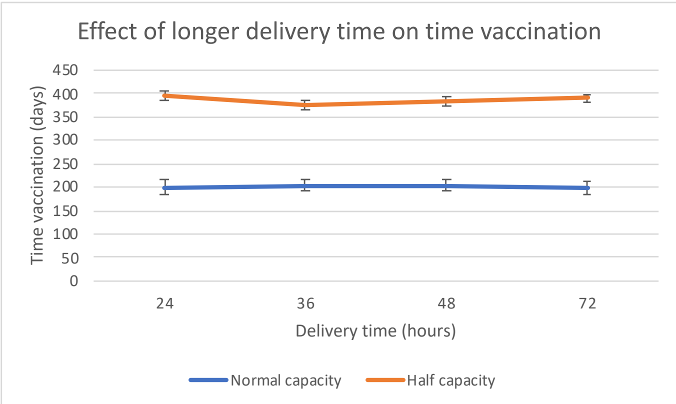


Figure 23: Effect of longer delivery time on time vaccination

Longer delivery times do not influence the time to vaccinate the population. This is in line with the expectations, because a longer delivery time just requires the doctors to place larger orders. However, longer delivery times increase the waiting time of patients after they made their first appointment. Therefore, the satisfaction decreases when longer delivery times are introduced. The effect on satisfaction is presented in Figure 24.

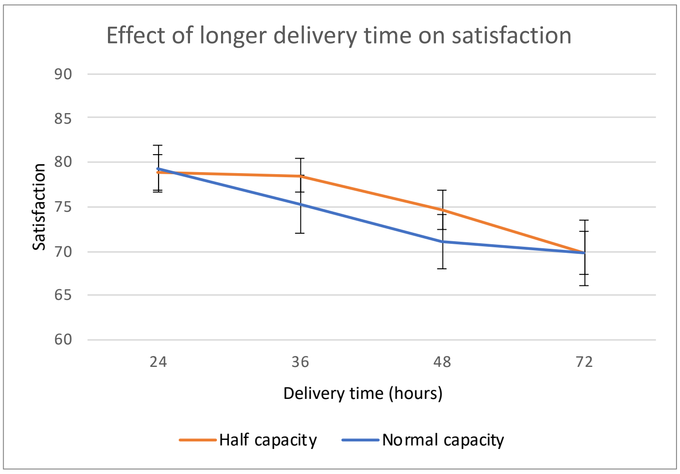


Figure 24: Effect of longer delivery time on satisfaction

From the graph in Figure 24, we can observe that a longer delivery time has quite a big impact on satisfaction, while half injection capacity does not cause less satisfaction in comparison with full capacity. This is a result of the fact that satisfaction is influenced by waiting time after making a first appointment, but not by waiting time until making the first appointment. However, this weaker performance is expressed in time to vaccinate the population, as shown in Figure 23. In the real world, waiting times caused by extra delivery time might be longer, so satisfaction might be even lower.

5.4.2 High service levels

In order to introduce high service levels, the injection capacity of doctors was increased and plenty vaccines were available, so that the injection capacity was not constrained by the availability of vaccines. The effect of additional injection capacity on satisfaction is displayed in Figure 25.

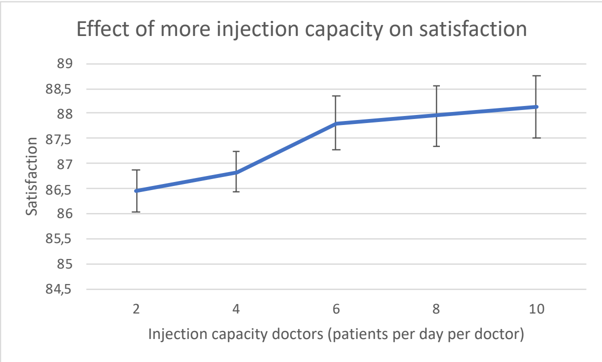


Figure 25: Effect of more injection capacity on satisfaction

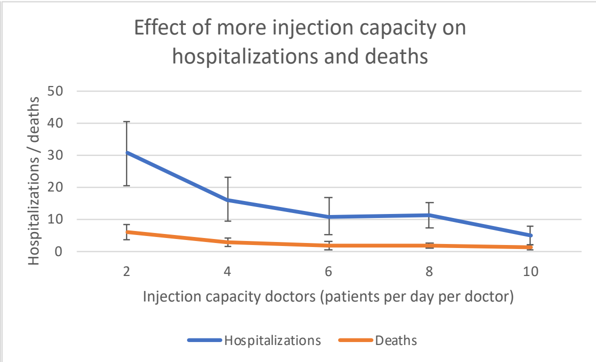


Figure 26: Effect of more injection capacity on hospitalizations and deaths

The effect on satisfaction is very limited. When the injection capacity is multiplied by five, satisfaction just increases with 1.6. This can be explained by the decrease of hospitalizations and deaths, shown in Figure 255. When a patient goes to hospital or dies, the willingness to vaccinate / satisfaction of patients in the same group of contacts increases. As a result, the increase of satisfaction / willingness to vaccinate variable is limited when less patients go to hospital or die. However, extra capacity has a big impact on the time to vaccinate all patients. This effect is presented in Figure 27.

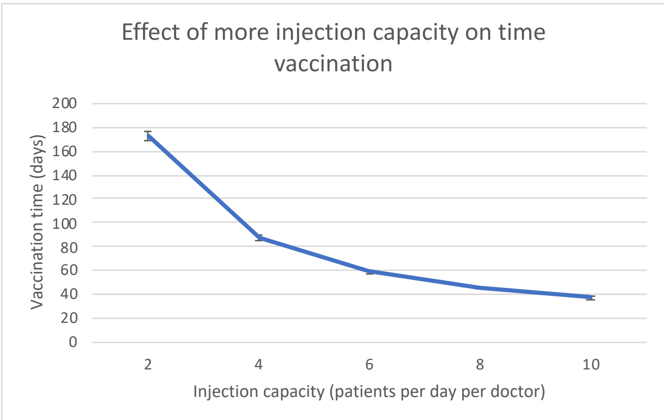


Figure 27: Effect of more injection capacity on time vaccination

Adding injection capacity enables doctors to inject more patients per day, so it takes less time to vaccinate all patients. This is not surprising, but in contradiction to previous experiments, we see a decrease in infections. The development of infections is shown in Figure 28. Although the error bars are still large, especially when the injection capacity is low (and therefore the vaccination time), additional injection capacity has unambiguous effect on infections.

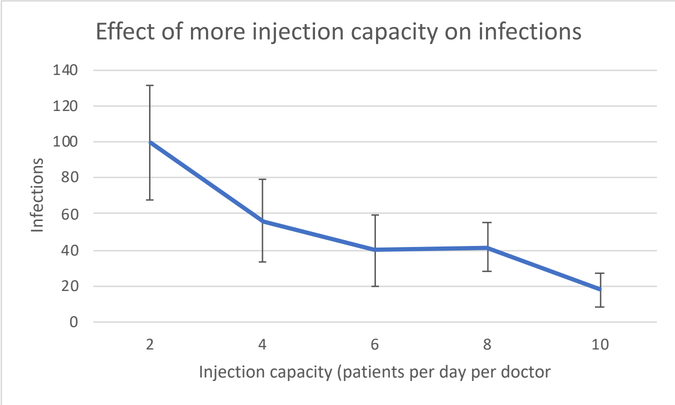


Figure 28: Effect of more injection capacity on infections

From this experiment, several conclusions can be drawn. Extra injection capacity has a small effect on satisfaction / willingness to vaccinate, but the effect is limited due to a decrease in hospitalizations and deaths, which cause an increase in willingness to vaccinate / satisfaction. Additional capacity causes a shorter vaccination time and when the vaccination time decreases significantly in comparison with the vaccination time in the other experiments, a steady decrease of infections can be observed. However the model seems not reliable to analyze the development of infections, it seems more accurate when the vaccination time is decreased significantly.

5.5 Scenarios in which the willingness to vaccinate / satisfaction decreases to a critical value (RQ 4 and 5)

For this last experiment, all parameters that have a negative influence on willingness to vaccinate / satisfaction are varied, in order to determine for which scenarios the willingness to vaccinate would drop to a value that herd immunity would not be achieved. These parameters are probability of delay, negative social influence and delivery time. The setup of parameters can be found in section 4.2.5.
For each scenario, the mean value of willingness to vaccinate / satisfaction is calculated. Since multiple variables are varied, the results will be presented in a table instead of a graph. The outcomes of all scenarios are presented in Table 13. Since estimations of the reproduction factor of the COVID-19 virus indicate that around 70% of the general population would need to be immunized before the circulation of the virus can be interrupted (Lippi & Henry, 2021), the scenarios that produce a mean willingness to vaccinate under 70% are marked in red.

Table 13: Mean willingness to vaccinate for different scenarios

Delivery time →		24 hours	36 hours	48 hours	72 hours
	Negative social influence ↓				
Probability delay 20%	4	79,0	79,8	75,3	75,7
	6	75,7	73,8	73,2	71,9
	8	71,6	69,3	67,4	63,8
	10	67,0	65,0	64,6	60,5
Probability delay 40%	4	72,2	72,2	68,3	70,5
	6	65,8	66,3	67,2	65,8
	8	62,3	59,9	58,8	56,1
	10	57,4	54,5	52,3	49,9

We see that combinations of negatively influencing factors often lead to an insufficient willingness to vaccinate. When the chance of delay is set to 20%, we see that the willingness to vaccinate decreases below 70%, if people would negatively influence each other with eight percentage point or higher (except for the scenario with a delivery time of 24 hours). If the chance of delay is increased to 40%, almost every scenario results in an insufficient willingness to vaccinate. Even when the negative social influence is set to 4 percentage points, all values approach the 70% threshold.

From this experiment, the conclusion can be drawn that combinations of negative factors often lead to a willingness to vaccinate below 70%, which is necessary to achieve herd immunity. Since almost every scenario in this experiment results in a value of willingness to vaccinate / satisfaction close to the threshold of 70%, this value might be under the threshold when simulated in the real sized model. However, these are combinations of abnormal values, so it is not likely that these scenarios will occur in the real world.

6. Discussion and limitations

The results have shown the effects of social influence and service level on the vaccination rate and the epidemic dynamics. These results will be discussed in a broader context in section 6.1. Section 6.2 discusses the implications of this research for policy making. Section 6.3 explains the limitations of the model. Section 6.4 reflects on the modeling assumptions. Section 6.5 reflects on the research approach and section 6.6 reflects on the modeling software.

6.1 Reflection on results

The results showed that the impact of social influence on the vaccination rate is limited. This is contradiction with the findings of Ni et al. (2021) whose simulations showed that the strength of social interactions among individuals has a considerable impact on vaccine coverage. This difference is possibly caused by the initial situation of the simulations in this research. The vaccination rate in the Netherlands increased to approximately 90% in the last 6 months (RIVM, 2021). Social interactions might have contributed a lot to the increase of the vaccination rate, when the average willingness to vaccinate was lower. The assumed high initial willingness to vaccinate in the simulations is justified, because this value is based on what we see in reality, but the high initial willingness to vaccinate minimizes the chance of people negatively influencing each other in the model. Despite this contradiction of results, it is plausible that negative effects of social interactions are limited when the average willingness to vaccinate is already high.
The same explanation applies to the limited effect of service levels. Making it easier for people to get vaccinated will lower the threshold to get a vaccine, but people who already have a positive attitude towards vaccinations will not be discouraged to get a vaccine when the waiting time is longer. This does not mean that high service levels are not important. Just like social interactions, the service level might have a bigger impact when the average willingness to vaccinate is lower. Just as mentioned by Eshun-Wilson et al. (2021), increasing the ease of getting vaccinated can contribute to the vaccination rate of hesitant people. In addition, high service levels lower the time to vaccinate the population and will reduce the number of infections. furthermore, maintaining a high service level increases the overall satisfaction of the population.

6.2 Implications for policy making

In this section, it will be discussed what the results of this research mean for policy making. Three policy implications will be discussed.

First, this research showed that GPs can take care of 11% of the vaccinations, provided that they are willing to spend one hour per day on vaccinations for 37 days. This is a significant part of the operation and seems feasible, despite the fact that many GPs indicate that vaccinating is not their task (Buckley, 2021). Therefore, it would be useful to discuss the possibilities with GPs and convince them to take part in the vaccination campaign. This would relieve the work that the GGD should execute in the future. Re-establishment of (some of) the current mass vaccination sites is another measure to let the vaccinations take place efficiently again.

Second, this research showed that the effect of social interactions and service level on the vaccination rate are limited, but it is still important take these effects into account, because they might be stronger when the willingness to vaccinate is lower. That will possibly be the case when we are not in a crisis situation anymore. Moreover, as mentioned in section 6.1, high service levels lower the time to vaccinate the population and will reduce the number of infections.

Third, the results showed that uncertainty in deliveries cause an increase in vaccination time. This should be considered when contracting vaccine suppliers. Reliable supply will make it much easier to control outbreaks.

6.3 Limitations of the model

The model was useful to investigate the effects of social interactions service level and uncertain deliveries on the vaccination rate and the virus spread. However, there are three important limitations of the model.

First, the modeling assumption has been made that people make their definitive vaccination decision at the moment of making their first appointment. The service level of the vaccination system did not have any impact on the vaccination rate, since the impact of waiting time and canceled appointments on willingness to vaccinate only occur after making the first appointment. Therefore, it has been investigated what the impact of different scenarios is on the final value of willingness to vaccinate. The final value of willingness to vaccinate is an indicator for what the vaccination rate would have been if the vaccination decision would have been made at the moment of actual vaccination. However, the model is not used yet to simulate what the vaccination rate would be if the vaccination decision would have been made at the moment of actual vaccinations.
The willingness to vaccinate variable is influenced by canceled appointments and waiting time, so it is an indicator for satisfaction as well, that is expected to become higher when the service level increases. However, willingness to vaccinate also increases when someone in a patients' contact group dies or goes to hospital. Therefore, satisfaction, that is captured in the same variable as willingness to vaccinate, increases when people die or are being hospitalized. As a result, the satisfaction score of a better performing vaccination system which prevents deaths and hospitalizations is limited.

Second, the model appeared to be not so reliable on the number of infections. The effects of delay, delivery time, social influence and lower injection capacity on the number of infections were not unambiguous. Only in scenarios wherein the injection capacities was increased, a steady decrease in infections could be observed, while increasing negative factors in other experiments caused both positive and negative effects on the number of infections (see section 5.3, Figure 22 for example). However a plausible effect on infections was observed in the experiment with higher injection capacities, the 95% confidence intervals of the mean values were very large, so the accuracy of those mean values is low.

Third, the model is very large, so it was necessary to scale the model down in order to reduce running time. Comparisons have been made between the real sized model and the scaled model. Some of the outputs were similar, but other outcomes showed differences in values. Some assumptions had to be made to translate the results of the scaled model to outcomes for the real sized model, which reduced the reliability of the conclusions.

6.4 Reflection on modeling assumptions

It is impossible to build an exact replica of the real world system. Therefore, several assumptions and simplifications must be made when attempting to approach the reality. The complete list of assumptions can be found in section 3.5.4. The assumptions that leave out some effects that could possibly occur in reality will be discussed in this section.

- **On the first moment that a patient is able to make an appointment, the patient decides whether he will get vaccinated. This decision does not change anymore.**

By implementing this modeling assumption, the service level does not have any impact on the final vaccination decision, since the effects of service level occur after making the first appointment. This is a limitation of the model and is explained more extensive in section 6.3.

- **Vaccines are restocked at the central vaccine stock at the end of every week. This is a fixed amount of vaccines, that equals the injection capacity of the doctors. There is a chance of delay. The duration of the delay is random with a maximum of four weeks.**

  The amount of vaccines that is delivered every week was fixed to the weekly injection capacity, in order to ensure that a delay would cause an immediate shortage of vaccines. However, batches of vaccines will be larger than weekly injection capacities (Rijksoverheid, 2021), so a delay would not always have an immediate effect on the vaccinations, but will have a bigger effect on the longer term.

- **Hospitalization of a contact within a patients group causes an increase of 5% of willingness to vaccinate. Death of a contact results in 15% additional increase of willingness to vaccinate.**

  Hospitalization or death of a friend as a consequence of a COVID-19 infection will let people with a negative attitude towards vaccination rethink their thoughts, because such events come very close. The values of 5% and 15% are used in order to take this effects into account in the model. There are two implications with these values. First, in the model, these values are the same for every patient, while different people are not equally sensitive to such events in reality. Second, these values are not based on any data, but on considerations of the author, so these values might be different in reality. This would possibly cause different developments of willingness to vaccinate in the real system.

- **The utilization of vaccines is 100%. There are no vaccines being wasted.**

  This is a major simplification of the real world system. Although vaccine wastage is limited in the last couple of weeks, a lot of vaccine were being wasted due to no shows of people that were expected to get their vaccine (RTL Nieuws, 2021). Eventual vaccine waste is not considered in the model, while this is also a metric of performance of the real system.

6.5 Reflection on research approach

Agent-based modeling is a suitable method for modeling system behavior, dependent on interactions between agents in the system. It is a useful tool to investigate emergent patterns in overall system behavior, that are not recognizable when considering the behavior of a single agents. However, it has some limitations. As mentioned in section 6.3 and 6.4, simulation models require some assumptions. As a result, the model outcomes are very conditional. The effects that are observed are valid, provided that a couple factors are as we assume them to be.

A second limitation of the research method is that executing proper validation of explorative models is difficult, especially when the time to do the research is limited. It is impossible to form a hypothesis, perform a real world experiment and see if the theoretical model outcomes correspond with reality (Nikolic, 2013). Another difficulty in validating ABMs is that they often involve human agents, with potentially irrational behavior, subjective choices and complex psychology. These are factors that are often hard to quantify (Bonabeau, 2002).

For this research, two validation experiments were performed (see section 3.8) to compare the model behavior with the real world system. These experiments indicate that the model has a sufficient accuracy within the domain of applicability of the model, but this conclusion is based on observations on the real system of the past couple of months, while the model aims to predict future system behavior. This makes it difficult to validate the model behavior.

If the time frame for this research was longer, additional validation techniques could have been applied. The model has been tested on face validity by the author, but an author might tend to see what he wants to see. Therefore, a better way of face validation is face validation by domain experts and problem owners. In this way, the behavior of agents, patterns of system behavior are discussed with knowledgeable people in the domain. Nonetheless, there are some issues with face validation by experts as well. Experts may understand what has happened but not what may happen, rely on their own internal models of system behavior to estimate possible futures and may also be subjective, biased and flawed in various degrees. Additionally, the selection of experts might be biased by looking for experts to validate the model who already agree with the type of outcomes created (Nikolic, 2013).

6.6 Reflection on modeling software

Netlogo is an easy accessible modeling tool to construct an agent-based model and is very suitable to visualize the model behavior. It is commonly used to model relatively simple systems on a small scale, to easily demonstrate emergent patterns that arise from interactions between agents. Although Netlogo was adequate to build this model and do the experiments with, the model was running very slow. Therefore, the model was scaled down in order to reduce running time, but even when the model was downsized, the execution time of a single run was still about 20 minutes. Several model outcomes did not have a high accuracy, so it would have been desirable to run more replications per experiment. Therefore, when large scale experiments must be run, I would recommend to choose another modeling tool that is more capable of running large models with a high number of agents.

In the next section, the conclusion of this research will be presented, as well as some policy recommendations and suggestions for further research.

7. Conclusion and recommendations

In this chapter, the findings of this research will be summarized. Because of the assumption that people make their vaccination at the moment of making their first appointment, the vaccination rate hardly decreased in any scenario. Therefore, the effects on the variable willingness to vaccinate / satisfaction, which is influenced by social interactions and service level, were investigated. The final value of willingness to vaccinate is an indicator for what the vaccination rate would be when the vaccination decision was made at the actual moment of vaccination.
The sub research questions will be answered in section 7.1. The answer on the main research question can be read in section 7.2. Section 7.3 provides some policy recommendations. Section 7.4 and 7.5 discuss the scientific and societal contribution of this research. The final section 7.6 of this chapter discusses some suggestions for further research.

7.1 Answers on sub research questions

1. What is the impact of uncertain vaccine deliveries on the time to get the population vaccinated and the vaccination rate?

The simulation showed that the vaccination time increases when delays are introduced. 20% chance of delay results in approximately three extra weeks of vaccination time. This comes down to an increase of 11%. When another 10% chance of delay is added to the simulation, the vaccination time increases with another 30 extra days. 40% chance of delay causes a decrease of less than 2% of willingness to vaccinate / satisfaction in comparison with the scenario without delays.

2. What is the impact of negative social influence on the vaccination rate?

When the weight of negative social influence is increased, we observe a steady decrease in willingness to vaccinate / satisfaction. When social influence is increased from 0 to 10, a decrease in willingness to vaccinate / satisfaction of 5 percentage point can be observed. This can be considered as a limited effect, because a value of 10 for social influence is a lot. When negative social influence is increased in combination with 20% probability of delay, the effect of an increase from 0 to 10 increases to 6.7 percentage point. Delays decrease the willingness to vaccinate / satisfaction, so the chance of negatively influencing another patient becomes higher when delays are introduced.

3. What is the impact of the service level of the vaccination system on the vaccination rate?

Service level is determined by waiting time, eventual canceled appointments and injection capacity. A lower injection capacity does not decrease individual satisfaction / willingness to vaccinate, but increases the vaccination time, which is an indicator for overall performance. An increase of delivery time (which is directly linked to waiting time from making an appointment till vaccination) from 24 hours to 72 hours, satisfaction / willingness to vaccinate decreases by 8 percentage point.

In scenarios of high service levels, with unlimited vaccine supply, no delays and short delivery times, satisfaction / willingness to vaccinate increased by 1.5 percentage point when the injection capacity of doctors increased from 2 to 10. This seems to be a limited effect, but in reality, this effect is bigger. The reason for this is that an individuals' willingness to vaccinate increases when someone in its contact group dies or goes to hospital. The extra injection capacity caused a strong decrease in vaccination time, infections, hospitalizations and deaths. Since willingness to vaccinate and satisfaction are captured by one variable, "satisfaction" increases less when less deaths and hospitalizations occur.

4. Under which circumstances of service level, negative social influence and uncertain deliveries will the vaccination rate drop to an insufficient value to achieve herd immunity?

The minimum willingness to vaccinate to interrupt the circulation of the virus is assumed to be 70% (Lippi & Henry, 2021). From the model simulations, we observed that the willingness to vaccinate decreases to values under 70% from a weight of negative social influence of 8 percentage point and more, in case of 20% chance of delay. When the chance of delay is 40%, willingness to vaccinate drops below 70% from a value of 6 for negative social influence and more.
The simulations were done with a scaled model. Compared to the real sized model, the scaled more reports much less failed vaccinations. Since almost every scenario in this experiment results in a value of willingness to vaccinate / satisfaction close to the threshold of 70%, this value might be under the threshold when simulated in the real sized model. However, these are combinations of abnormal values, so it is not likely that these scenarios will occur in the real world.

5. Which contribution can GPs make to the vaccination campaign, given the minimum required system performance to achieve herd immunity?

If GPs would take care of 100% of the vaccinations, it is achievable to remain the willingness to vaccinate above 70%, because only really bad scenarios that assume negative social influence to be abnormally large result in values of willingness to vaccinate below 70%. However, this performance would not be sufficient to control the number of infections and the vaccination times in these scenarios vary from 6 months to even more than a year. General practitioners would have to inject 36 patients per day to achieve an infection ratio of 2.8% of the population.

The model seemed not reliable to evaluate the effects of different scenarios on the number of infections, since the 95% confidence intervals appeared to be very large and simulations did not generate unambiguous effects on the number of infections. However, when the injection capacity increased the number of infections show a steady decrease. When the injection capacity is increased to 6 in the scaled model, the number of infections decreased to 40, which comes down to 2.8% of the population. When we translate this injection capacity to the real sized model, a total of 180 patients per day must be vaccinated to achieve these infection numbers. According to general practitioner Fränk Ritter, 4 patients per hour can be vaccinated at the general practice. That means that general practitioners can take care of 11% of the vaccinations, provided that they accept to invest 1 hour per day on vaccinations for 37 days.

7.2 Answer on main research question

Using the answers on the sub research questions, the main research question can be answered. The main research question was:

What is the required performance of the vaccination system to keep the vaccination rate above a sufficient level and minimize virus spread, given uncertainties in vaccine supply and negative social influence regarding vaccinations?

The vaccination rate in the Netherlands is about 90% at the moment (RIVM, 2021). Therefore, there are not many people with a negative attitude that would negatively influence someone towards vaccination. The experiments showed that the vaccination rate would remain above 70%, even in scenarios where the performance of the vaccination system was very poor. Only in scenarios where waiting time, delays and abnormal values for negative social influence where combined, the vaccination rate would decrease below 70%. This was observed from a weight of negative social influence of 8 percentage point and more in case of 20% chance of delay. When the chance of delay is 40%, willingness to vaccinate drops below 70% from a value of 6 for negative social influence and more.

However the model seemed not reliable to evaluate the effects of different scenarios on the number of infections, a steady decrease in infections was observed when the injection capacities were increased. This is caused by the strong decrease in vaccination time, because less time to vaccinate the population means less chance for the virus to spread. When the injection capacity was increased to 6 in the scaled model, the number of infections decreased to 40, which comes down to 2.8% of the population. When we translate this injection capacity to the real sized model, an injection capacity of 180 patients per day is required to achieve these infection numbers. That means that general practitioners can take care of 11% of the vaccinations, provided that they accept to invest 1 hour per day on vaccinations for 37 days.

From these main findings of this research, the conclusion can be drawn that the minimal required performance of the vaccination system to keep the vaccination rate above a sufficient level is low. However, this performance would not be sufficient to control the number of infections and the vaccination times in these scenarios vary from 6 months to even more than a year. As earlier mentioned, 180 patients per day must be vaccinated in the neighborhood to achieve an infection ratio of 2.8% of the population. This number is even very high when this many infections occur within 60 days, considering the fact that about 10% of the Dutch population got infected in 16 months of pandemic.

7.3 Policy recommendation

Based on the findings of this research and insights of general practitioners, I would recommend to focus on higher vaccination capacities in order to reduce the vaccination times and limit infections. Collaboration with reliable suppliers of vaccines will also contribute to reducing the vaccination time.
Despite the fact that vaccinations can be executed more efficiently by GGDs, the additional force of the GPs can be useful. GPs can take care of 11% of the vaccinations, provided that they accept to invest 1 hour per day on vaccinations for 37 days. Therefore, convincing GPs to take part in the vaccination campaign can help to relieve the GGDs. Re-establishment of (some of) the current mass vaccination sites would be a useful option to enable GGDs to work efficiently.
Although this research showed that the effect of social interactions and service level on the vaccination rate are limited, it is still important take these effects into account, because they might be stronger when the willingness to vaccinate is lower. That will possibly be the case when we are not in a crisis situation anymore.
Further research, suggested in section 7.6, will provide more accurate and detailed knowledge on this topic.

7.4 Scientific contribution

Agent-based modeling has been widely used for different purposes in researching topics regarding the COVID-19 pandemic (see section 2.1.2.6), such as vaccination strategies and epidemic dynamics. Several social studies have been conducted towards willingness to vaccinate (for example; Mouter et al., 2020 and RIVM, 2021) and different measures have been taken for target groups with a low willingness to vaccinate, in order to increase the ease of getting vaccinated (NOS, 2021b). However, the interactions of the concepts of willingness to vaccinate, social influence and service level have not been combined in simulation study yet. This research provided some insights in how these concepts interact with each other and why the KPIs of this system increase or decrease. This research showed that the willingness to vaccinate of a country with an already high willingness to vaccinate is very robust. Enormous increases in negative social influence, delays and low service levels didn't cause significant disruptions of the willingness to vaccinate.
Although the effects on infections turned out to be inaccurate, the proposed model can be improved and can form a good basis for further research (see section 7.6).

7.5 Societal contribution

The COVID-19 pandemic caused a global health and economic crisis. Vaccinations are an important part of the exit strategy. Now that the vaccines are available and being distributed, it is important to explore the next steps. Future scenarios in which recurring vaccinations in the future are necessary are not unlikely, since it is still unclear for which time period the vaccines offer protection to the virus and new virus mutations. This research contributed to the knowledge about requirements for a good vaccination strategy for recurring vaccinations. The experiments showed that the vaccination rate is likely to remain above the 70% threshold, even if only general practitioners would take care of the vaccinations, but a short vaccination time is necessary to control the number of infections. This research made clear that GPs can realize a significant contribution to the vaccination campaign. However, they should first be convinced to take part in the vaccination campaign, since many GPs are not willing to do so.

7.6 Suggestions for further research

I have three suggestions for further research on this topic. The first suggestion for further research is making improvements in the model. The model can be extended by adding a functionality to change the moment of deciding whether to get a vaccine or not, in order to make it possible to get better insights in the effects of the service level of the vaccination system. The model can be improved by incorporating a more advanced and detailed epidemic model, in order to get more reliable simulations for investigating effects on infections.

The second suggestion is investigating how important social influence is for people when making a vaccination decision. If there is more knowledge available about this topic, the data can be incorporated in the model, rather than investigating "what if" scenarios.

The third suggestion is to execute the same experiments as done in this research, but with the amount of patients that currently get a flu vaccination. A possible future scenario is that only these people need recurrent vaccinations, just as for the influenza virus. In that case, general practitioners might be able to take care of these vaccinations.

These model improvements and investigation of social influence will enable researchers to draw more reliable conclusions about this topic. Simulating the situation with the number of patients that currently need a flu vaccination will provide insights in the extra workload for general practices when the situation occurs that only older and vulnerable people need additional vaccinations for COVID-19.

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Appendices

Appendix A IDEF0 scheme

IDEF0 is a methodology designed to model decisions, activities and actions within a process using a combination of graphics and text. The concept of IDEF0 is shown in Figure 29. The input is used, consumed or altered by the function. Controls are objects vital to produce an output, as they control the way the function is executed. Examples of controls are standards and regulations. Mechanisms support the execution of the functions. Examples of mechanisms are human resources and equipment (Lang et al., 2018). The IDEF-scheme gives insight in the needs and requirements, to successfully convert an input into a desired output.

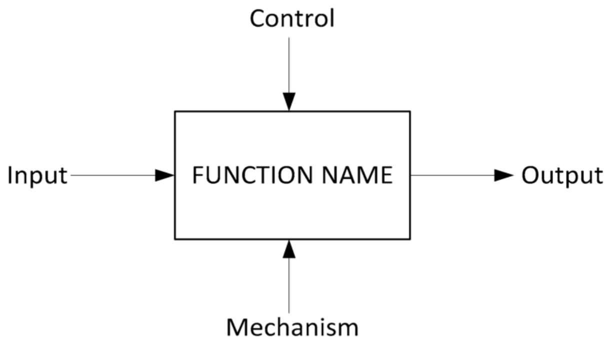

Figure 29: Concept of IDEF0

There are three main processes for the distribution of vaccines:

- Vaccinations at the GP (or at home)
- Administrative process
- Supply, transport and storage

Figure 30 provides an overview of the six sub-processes occurring within the vaccination process at the GP. Figure 31 shows the sub processes when the vaccination takes place at home, when a patient is not able to travel to the GP. Figure 32 presents the administrative process and Figure 33 outlines the processes regarding supply, transport and storage. The sub processes from these IDEF0 schemes that are incorporated in the model are linked to each other in Figure 10 (section 3.4.1).

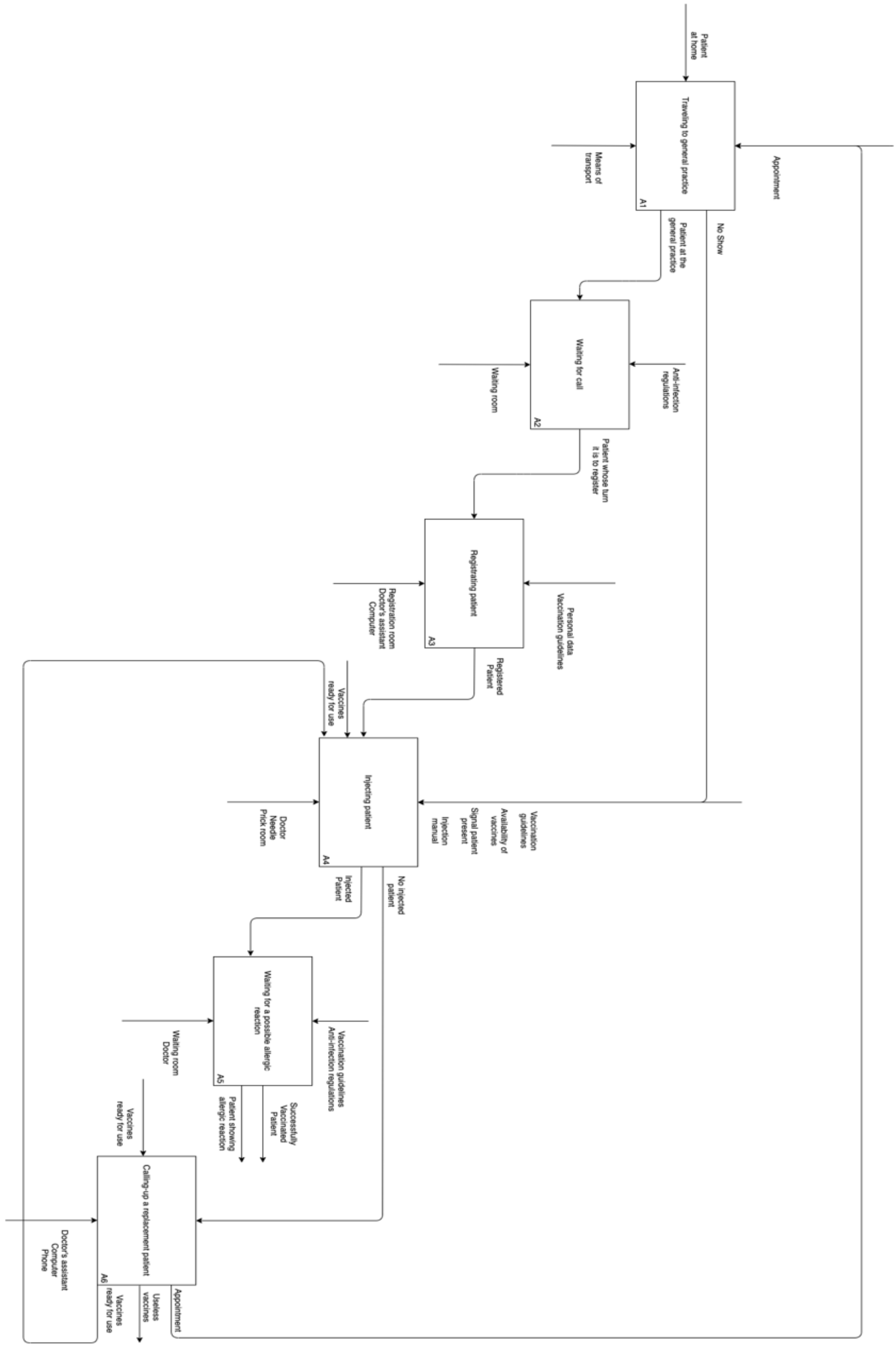

Figure 30: Vaccination process on A1 level

The vaccination process for a patient starts with traveling to the GP. This travel is triggered by an appointment. When a patient enters the general practice, he will be seated in the waiting room, until the doctor calls him up. There are anti-infection regulations in force to prevent spread of the disease where the patients are being vaccinated against. This constrains the number of people that can be seated in the waiting room.
The next step is the registration of the patient. It is important to register which vaccine the patient is getting, because for most vaccines, two inoculations are required for immunization to the disease. The type of vaccine depends on the population group wherein the patients belongs and is captured by the vaccination guidelines of the government. The resources needed for registration are a room, administration staff and a computer. It is desirable that doctors are not executing the registration their selves, because people who are authorized to inject the virus are scarce. The registrations thereby take more time than the injections, so it is efficient to have more administration staff than doctors.
The next process is the injection. A match between the presence of a patient and the availability of a vaccine is required to achieve a successfully vaccinated patient. On the one hand, the supply of new and scarce vaccines is uncertain. On the other hand, it often occurs that people don't show up when they have an appointment (RTL Nieuws, 2021). That is mainly caused by distrust, as a result of side effect cases. When a patient doesn't show up at their appointment, sub process A6 is triggered. If the assistant doesn't manage to find a replacement patient, the no show may result in wastage of vaccines.
After the injection, every patient has to stay at the practice for another 15 minutes, to ensure that medical help is available in case of allergic reactions. The number of people allowed in the room is constraint by anti-infection guidelines.

In some cases, patients are not able to come to the practice. In those cases, the vaccination must take place at home. An extra sub-process is needed for the vaccination, which makes it a lot more complicated and inefficient. The doctor has to travel to the patients' homes and transportation of vaccines can be difficult, since they must be transported carefully and cooled. Neglecting the transportation prescriptions may result in wastage of vaccines. Besides a match between availability of vaccines and presence of patients, the availability of a car with a sufficient cooling facility is a third component of the match that is required to achieve a successfully vaccinated patient, in case of home vaccinations. The IDEF0-scheme for home vaccinations is shown in Figure 31.

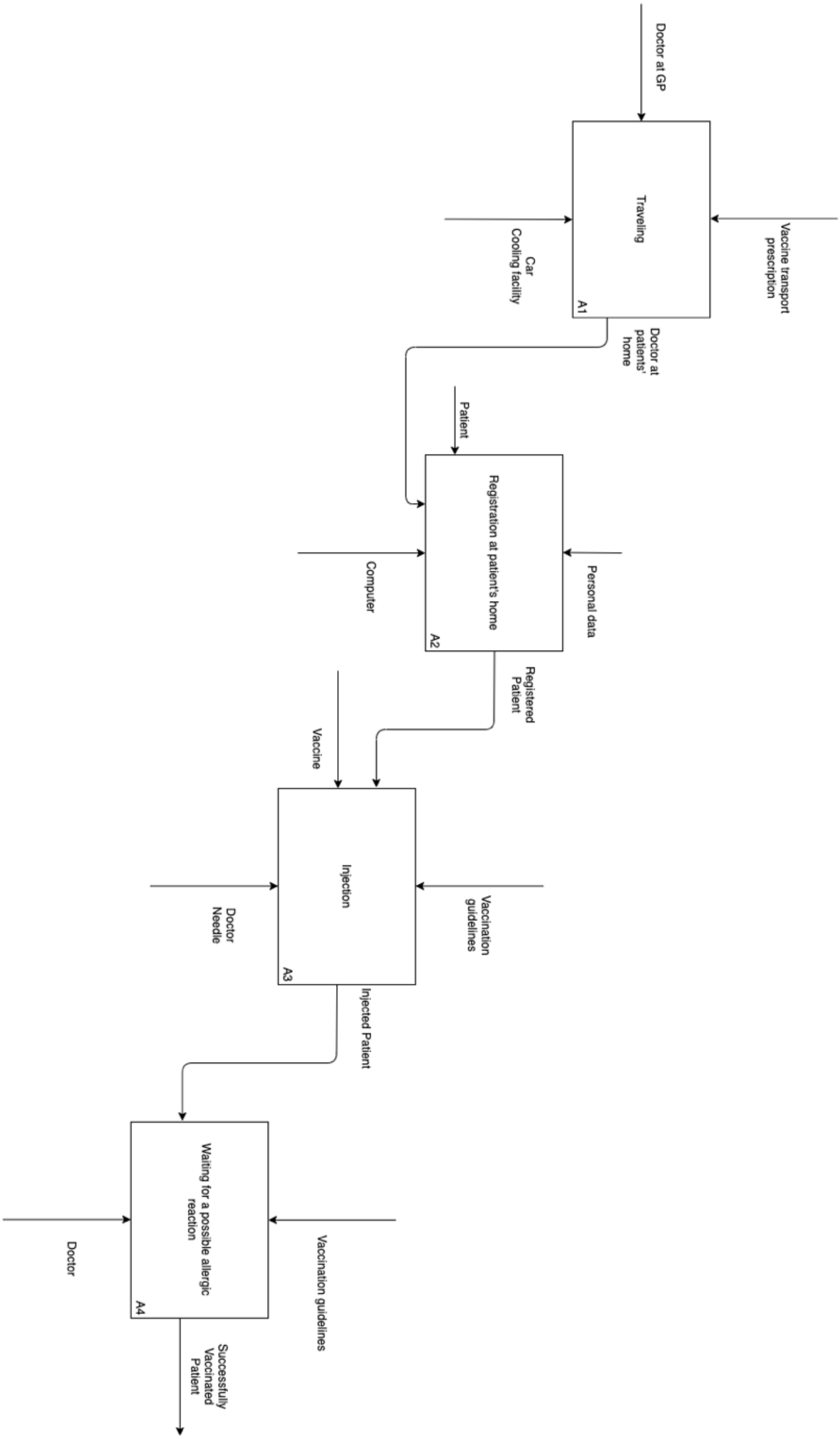

Figure 31: Vaccination process at home on A1 level

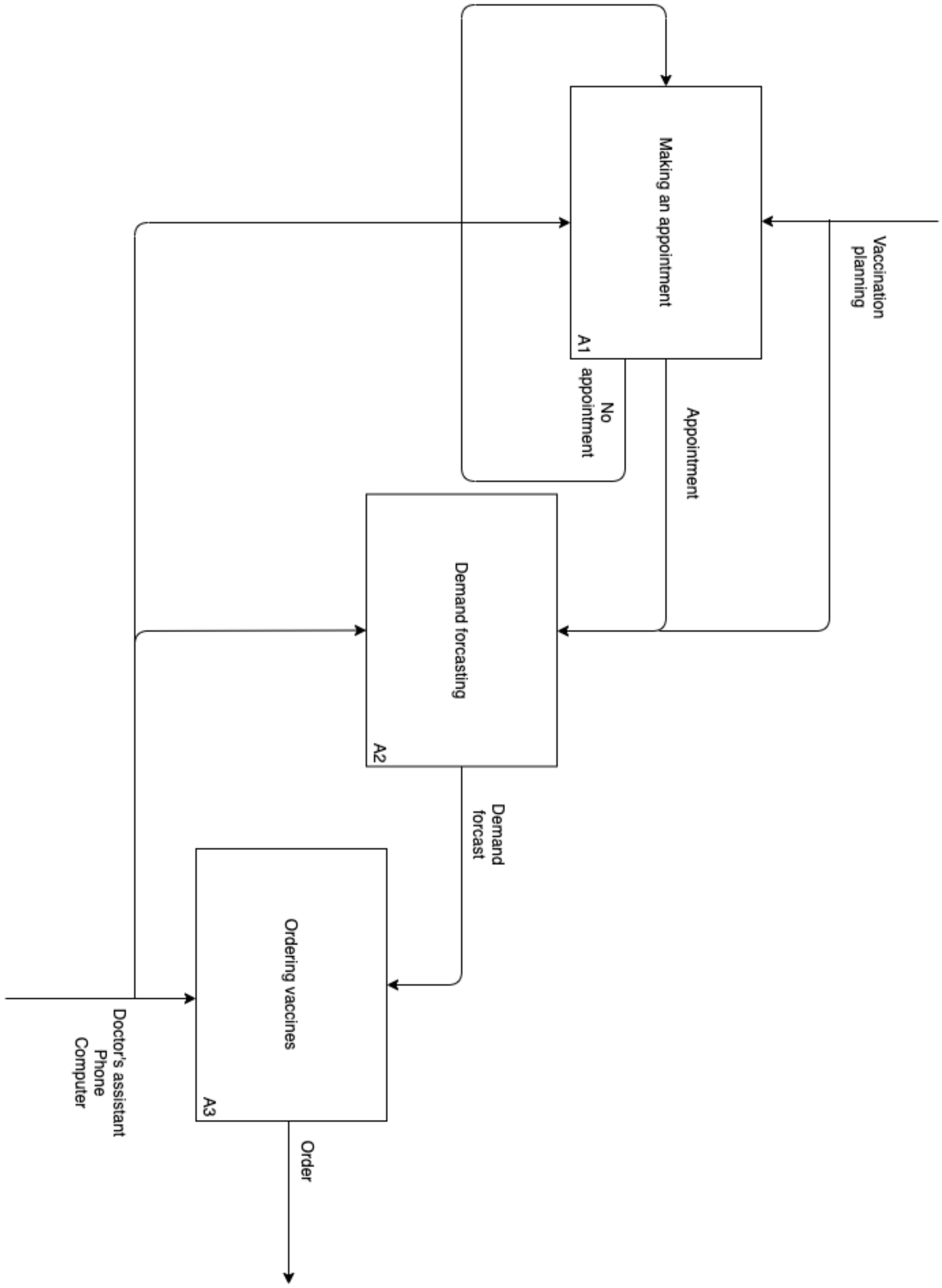

Figure 32: Administrative process on A1 level

Figure 32 shows the sub processes of the administrative process that is necessary to coordinate the vaccinations. Doctors' assistants need to schedule appointments. They are calling up patients on basis of the vaccination planning. The number of appointments is a source of information for the forecasting of the demand. On basis of the demand forecast, the correct amount of vaccines will be ordered. The outputs of the administrative process are appointments and orders. An appointment is the trigger for the vaccination process (Figure 30) and process A4 in Figure 33. The order is the trigger for process A2 in Figure 33, presented on the next page.

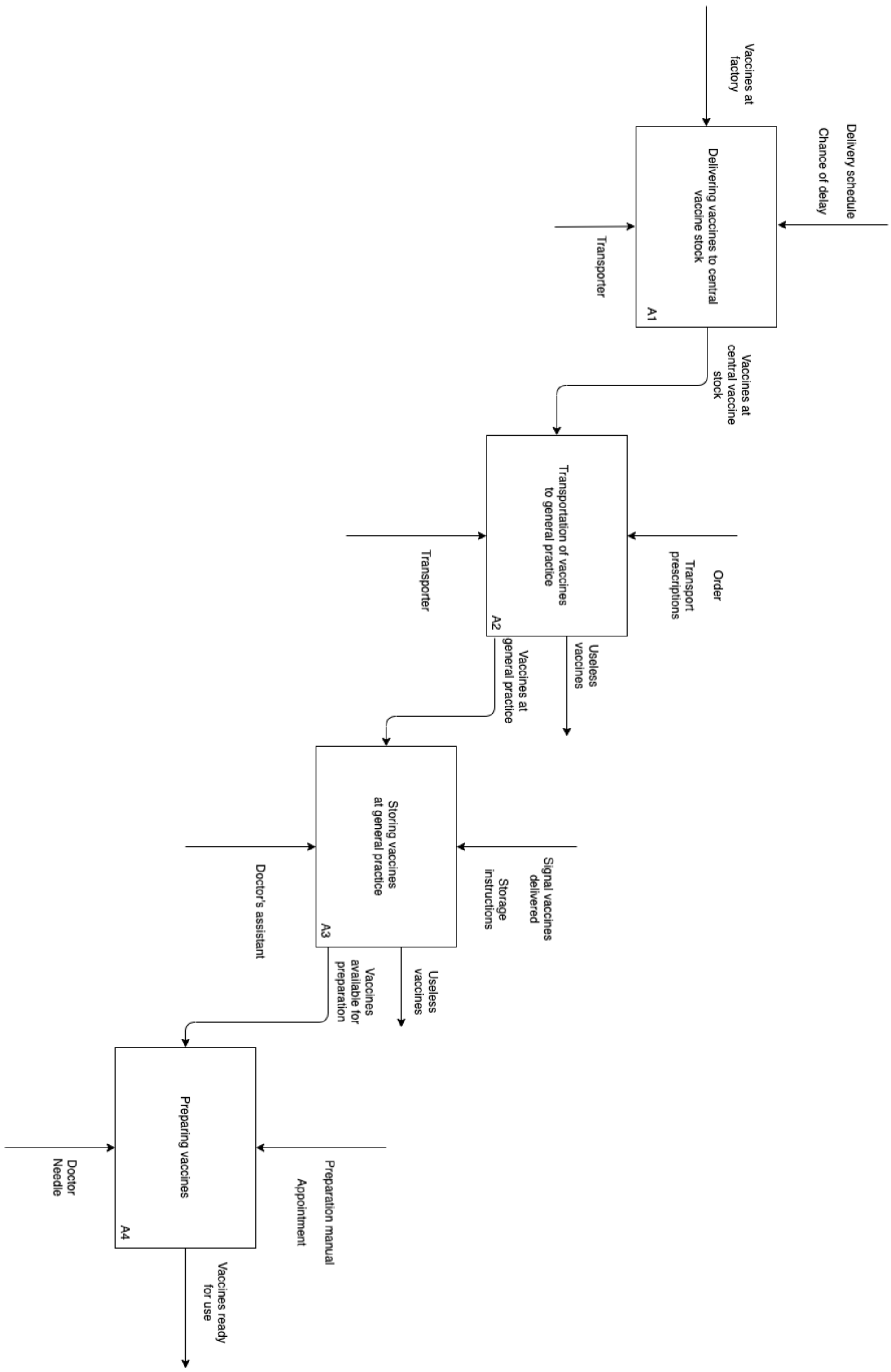

Figure 33: Supply, transport and storage of vaccines on A1 level

When a vaccine manufacturer delivers a batch of vaccines to a country, the vaccines are stored in a central vaccine storage. In the model, this is an external process. The transportation from the central vaccine stock starts when a doctors' assistant places an order. After delivery of the vaccines, they need to be stored at the GP. The vaccines need to be prepared before they can be administered to the patient. The amount of vaccines that need to be prepared depends on the number of appointment for that day. There are some guidelines for all these sub processes, in order to ensure that the vaccines remain in good condition. For all these processes, there is a chance of wasting vaccines, when they are not handled as prescribed.

Appendix B Parameters and KPIs

In this appendix, all model parameters and KPIs are listed and explained.

Parameters

Number patients: amount of patients in the simulation.

Number doctors: amount of doctors in the simulation.

Number assistants per doctor: amount of assistants at every general practice.

Initial central vaccine stock: number of vaccines that are available to order at the start of the simulation.

Initial number infected: number of patients that are infected with the virus at the start of the simulation

Virus spread chance: probability of infecting another patient when in contact.

Number groups: The amount of groups in the model determines the number of other patients that a patient will have contact with, influence and infect each other.

Percentage anti vaxxer: percentage of patients in the simulation that are against vaccination and have an initial willingness to vaccinate of 0.

Calling speed: number of ticks that an assistant needs to make an appointment.

Influence service: the number of percentage points that willingness to vaccinate / satisfaction will decrease after a failed vaccination. For example; if this value is set to 10, a patients willingness to vaccinate will decrease from 90 to 80 in case of a failed vaccination / cancelation of appointment.

Social influence: Every day, each patient creates a couple of contacts with other patients. A patients' willingness to vaccinate is the chance of positively influencing its contacts and 1 – willingness to vaccinate is the chance of negatively influencing its contacts. Social influence is the number of percentage points that the willingness to vaccinate of a patient increases or decreases when it is being influenced.

Influence anti-vaxxer: social influence of an anti vaxxer, only in a negative way.

Influence waiting time: number of percentage points that the willingness to vaccinate of a patient decreases per 24 hours of waiting between making a first appointment and vaccination.

Restock Pfizer, moderna, astrazeneca: fixed batch size of vaccines per manufacturer.

Probability delay: chance of delay for every delivery.

Delay Pfizer, moderna, astrazeneca: duration of delay, determined by a random number for every delivery, in case of delay with a maximum of 28 days.

Delivery time: time from ordering vaccines from the central vaccine stock to delivery at the general practice. This parameter is also used to determine the appointment date of a patient. The time between making an appointment and the appointment date is equal to the delivery time.

Safety waiting time: number of extra hours before the appointment date to prevent failed vaccinations.

Oude westen: presets the real world values of the Oude Westen.

KPIs

Vaccination rate: number of patients that took the vaccine, divided by the total number of patients. A patients' willingness to vaccinate at the moment that a patient makes an appointment for the first time is the chance of getting a vaccine.

Willingness to vaccinate / satisfaction: willingness to vaccinate and satisfaction are captured in the same variable, because the service level (i.e. waiting times, number of failed vaccinations) and social influence determine the willingness to vaccinate. The vaccination decision is made at the first time that a patient makes an appointment (see section 3.5.4), but willingness to vaccinate is not influenced by the service level at this moment, because the waiting time starts at this moment and a failed vaccination cannot occur before making the first appointment. At the moment of actually vaccinating, service level had an effect on willingness to vaccinate in the form of satisfaction. Willingness to vaccinate / satisfaction at the moment of vaccination is the chance of getting vaccinated, if the decision would be made at the moment of vaccination, after service level played a role in making the vaccination decision.

Ratio death: number of patients that died, divided by the total number of patients.

Infections: number of infections.

Hospitalizations: number of hospitalizations.

Failed vaccinations: number of vaccinations that did not take place because of unavailability of vaccines when the patient came to the general practice for its vaccination. A failed vaccination represents a canceled appointment.

Mean time from first appointment to vaccination: this is also the waiting time, i.e. the time from making the first appointment until the vaccination actually took place.

Appendix C Model verification

Model verification deals with building the model right (Balci, 1998). When a simulation language is used, verification is primarily concerned with ensuring that the model has been programmed correctly in the simulation language. The primary techniques used to determine that the model has been programmed correctly are structured walkthroughs and traces (Sargent, 2013). This has been widely done during the debugging of the model. Debugging identifies errors causing the model to fail and changes the model accordingly in order to correct these errors (Roungas et al., 2018). In addition, a couple of situations were set up for the model verification, with a low amount of patients, so that their functioning can easily be checked manually.

Verification experiment 1

In the first verification experiment, it will be verified that patients do not create more contacts than their maximum number of contacts per day, that they first try to create contacts within their own group before creating contacts with patients in other groups and that patients do not influence each other on willingness to vaccinate when they are isolated from each other.
The number of patients is set on 10 and the option to create contacts outside a patients' contact group is switched off. When the number of groups is set on 10, the patients do not create any contacts, because every single patient is a member of its contact group, without any others. In this case, the willingness to vaccinate does not change, because the patients do not create any contacts to recommend or discommend vaccination. If the number of groups is set on 5, the patients create contacts with other patients that belong to the same group and they do influence each other. There are no patients that exceed their maximum number of contacts per day. If the option to create contacts outside the patients' own group of contacts, inter-group contacts are created if there are no patients left within the patients' own group that have not reached their maximum number of contacts.

Verification experiment 2

In the second experiment, it was examined whether the doctors utilize their full capacity per day. Firstly, 60 patients are set up. Every tick, a doctor should call up a patient, until the full capacity per day is reached. The sum of injection capacities of all doctors is 20 vaccinations per day. When running the model, the counter of appointments made today stops at 20 appointments, so that works correctly. In order to prevent over ordering by doctors, they should adjust their injection capacity when there are less patients to be vaccinated left than the injection capacity. On day 2, doctor 0 and doctor 1 only have 2 patients left that are willing to vaccinate. Both of them adjusted their injection capacity to 2 and the counter of appointments made today stops at 16 appointments, that equals the total injection capacity on this day. On the next day, the counter of vaccinations done today adds up to 16. For the next couple of days, both the appointments made and the number of vaccinations executed are equal to the injection capacity. Therefore, it can be concluded that the doctors utilize their full capacity every day.

Verification experiment 3

The third experiment is about influencing patients on their willingness to vaccinate. At the setup patients are set up willing to vaccinate, not willing to vaccinate or as a doubter, depending on their age group a chance to belong in one of those three groups. Patients who are not in doubt, should not be influenced by social contacts. They can only change their willingness to vaccinate if they experience a long waiting time or a failed vaccination, or when someone in their group of contacts goes to hospital or dies after infection. This is tested by inspecting one doubter and one non-doubter in the same group of contacts. If the command "recommend-or-discommend" is executed, the willingness to vaccinate of the doubter changes and the willingness to vaccinate of the non-doubter does not. However, when the risk of death and hospitalization of the doubter is set to 100% after infection and the doubter goes to hospital and passes away, the willingness to vaccinate of the non-doubter increases. When a single patient is sent to the doctor for vaccination, the willingness to vaccinate, which is also the chance to recommend vaccination to others, increases in case of a successful vaccination and decreases in case of a failed vaccination. From these tests, the functionality of influencing patients on their willingness to vaccinate appears to be working properly.

Appendix D Model validation

Model validation deals with building the right model. Model validation substantiates that the model behaves with satisfactory accuracy, so that the approach of reality is sufficient, within the domain of applicability of the model.

Comparison of parameter effects to expectations from the real system

For the first validation experiment, the face validity of the model will be examined. To test the face validity, it is tested if there exist a reasonable fit between the feedback structure of the model and the essential characteristics of the real system (Martis, 2006). It will be checked whether an increase or decrease of some model parameters cause the expected effect on model outputs, based on system behavior developments in the real world.
The technique of Assertion Checking checks if something is happening opposed to what the modeler assumes that should happen, thus detecting potential errors in the model (Balci, 1998). The reference setting and output are as follows:

Table 14: Reference setting and output

Parameter	Reference Value	Parameter	Reference Value	Output variable	Output value
Number-patients	100	Restock-moderna	6	time to vaccinate population	48
Number doctors	3	Restock-astrazeneca	4	Failed vaccinations	7
Injection-capacity-doctors	1	Safety-waiting-time	0 hours	infections	8
Initial-central-vaccine-stock	20	Social influence	2	hospitalizations	1
Number-groups	10	Influence service	10	Number of deaths	0
Delivery-time	24 hours	Influence waiting time	2	Ratio deaths	0
Initial-number-infected	2	Percentage anti-vaxxer	0	Ratio vaccinated	0.92
Virus-spread-chance	35%	Influence anti-vaxxer	0	Ratio not willing to vaccinate	0.08
Probability-delay	0%	Random seed	0	Time from first appointment to vaccination	45 hours
Restock-pfizer	10			Willingness to vaccinate / satisfaction	91.71

In the Table 15, the variables that were adjusted and their impact on the model outputs are presented. The change of the model outputs are expected to be influenced are listed for some of the parameters. A '+' indicates an expected increase, a '-' an expected decrease and a '0' indicates that the variable is not expected to change. The unexpected changes in variables are explained under the table.

Table 15: Adjusted variables and effects

Parameter	Change in value	Model outputs	Expectation	Change in value	According to expectation?
Number patients	100 → 200	Time to vaccinate population	+	48 → 89 days	Yes
		Failed vaccinations	+	7 → 9	Yes
		Infections	+	8 → 29	Yes
		Hospitalizations	+	1 → 14	Yes
		Vaccination rate	-	0.92 → 0.93	No
		Satisfaction	-	91.71 → 90.96	Yes
Injection capacity doctors	1 → 3	Time to vaccinate population	-	48 → 34 days	Yes
		Failed vaccinations	0	7 → 68	No
		Infections	-	8 → 9	No
		Hospitalizations	-	1 → 3	No
		Vaccination rate	+	0.92 → 0.93	Yes
		Satisfaction	+	91.71 → 80.85	No
Initial number infected	2 → 10	Infections	+	8 → 57	Yes
		hospitalizations	+	1 → 17	Yes
		Number deaths	+	0 → 2	Yes
		Vaccination rate	+	0.92 → 0.93	Yes
Virus spread chance	35% → 60%	Infections	+	8 → 62	Yes
		hospitalizations	+	1 → 28	Yes
		Number deaths	+	0 → 1	Yes
		Vaccination rate	+	0.92 → 0.95	Yes
Delivery time	24 hours → 72 hours	Time to vaccinate population	+	48 → 51 days	Yes
		Time from first appointment to vaccination	+	45 → 125 hours	Yes
		Failed vaccinations	0	7 → 17	No
		Satisfaction	-	91.71 → 88.1	Yes
		Vaccination rate	-	0.92 → 0.91	Yes
Safety waiting time	0 hours → 24 hours	Time from first appointment to vaccination	+	45 hours → 60 hours	Yes
		Failed vaccinations	-	7 → 5	Yes
Probability delay	0% → 100%	Time to vaccinate population	+	48 → 53 days	Yes

		Failed vaccinations	+	7 → 19	Yes
		Vaccination rate	-	0.92 → 0.93	No
		Time from first appointment to vaccination	+	45 → 77 hours	Yes
		Satisfaction	-	91.71 → 91.24	Yes

Most of the changes in model outputs represent the expected behavior of the model. However, there are some outcomes that are not logical and need some explanation:

- The high number of extra infections after doubling the number of patients is caused due to lack of vaccines. In the experiment, the initial central vaccine stock and the restock did not grow with the number of patients, so the virus had more time to spread before patients were able to get vaccinated. The effect of additional hospitalizations was bigger than the effect of additional failed vaccinations. As a result, the vaccination rate increased.
- The limited positive effect of additional injection capacity is caused due to lack of vaccines as well. The real injection capacity cannot increase to the same level of the potential injection capacity when there are not enough vaccines available. The huge increase in failed vaccinations is a result of doctors who call up an amount patients depending on their injection capacity. However, they cannot fulfill the vaccinations without a proper amount of vaccines.
- The additional injection capacity also caused a decrease in satisfaction. This can be explained by the amount of failed vaccinations, which has a negative impact on willingness to vaccinate. The additional failed vaccinations had a large impact on the average time from first appointment to vaccination. The overall vaccination time decreased, but some individuals were not vaccinated for a longer time. This explains the increase in infections and hospitalizations.
- The number of failed vaccinations was not expected to increase after an increase of the delivery time, since patients are called up later when the delivery time is longer. However, doctors are ordering more vaccines (for more days at once) if the delivery time is longer. The vaccine stock did not allow doctors to order more, because the stock did not grow with the bigger orders. This resulted in patients being called up, without a sufficient vaccine inventory at the general practices.
- The increase of the virus spread chance caused a decrease in deaths. This happened by coincidence. After trying a different random seed, the numbers came out in a logical way.
- The delays of restock had limited effects. This can be explained by the fact that the amount of delay per supplier is fixed. Therefore, there are delays experienced in the first week of the run, but after the first delivery, the batches are delivered on regular basis, so the central vaccine stock remains on the right level. The delays should be more uncertain, so therefore the delays are re-programmed and are now determined by a random number, with a maximum of four weeks. The outcomes of the run with the revised code are presented in the Table 16.

Table 16: Adjustment of probability delay after code revision

Parameter	Change in value	Model outputs	Expectation	Change in value	According to expectation?
Probability delay	0% → 100%	Time to vaccinate population	+	48 → 85 days	Yes
		Failed vaccinations	+	7 → 43	Yes
		Vaccination rate	-	0.92 → 0.93	No
		Time from first appointment to vaccination	+	45 → 185 hours	Yes
		Satisfaction	-	91.71 → 85.4	Yes

The vaccination rate increased when delays are introduced in the run, while the satisfaction decreased. This is a consequence of the following rule in the model: patients decide whether they are going to get vaccinated at the first time that they make an appointment. A delay causes cancelation of appointment, the patient will not change his vaccination decision. However, the satisfaction is able to decrease after making the first appointment. That is the reason that the satisfaction dropped, but the vaccination rate did not. The slight increase of vaccination rate can be explained by the increase in hospitalizations.

Appendix E Parameter setup

Scaled model

A couple of runs will be done to compare the scaled model with the real sized model. The parameter setup for both models is outlined in this section.

First, the model will be run with 8370 patients, according to the number of inhabitants in Oude Westen, to explore the outcomes. The probability of delay will be varied from 0 to 100 with intervals of 20. Because of the long running time, each variation of input will be run just once.

Table 17: Parameter setup real sized model

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
Number-patients	8370	Probability-delay	0 – 20 – 40 – 60 – 80 – 100	Social influence	2	Safety-waiting-time	5
Number doctors	5	Restock-pfizer	250	Influence service	10	Delivery-time	24
Injection-capacity-doctors	12	Restock-moderna	100	Influence waiting time	2	Percentage anti-vaxxer	14
Initial-central-vaccine-stock	420	Restock-astrazeneca	100	Number-groups	100	Influence anti-vaxxer	3
Initial-number-infected	5	Virus-spread-chance	15	Random seed	0	Replications	1

The output of the model settings above will be compared to the model output of some runs with 1/6 of the number of patients. For these runs, the availability of vaccines and injection capacity of the doctors will be scaled down with the same factor. The adjusted values are shown in the Table 18. The other values remain the same as in the real sized model.

Table 18: Parameter setting scaled model

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
Number-patients	1395	Probability-delay	0 – 20 – 40 – 60 – 80 – 100	Restock-astrazeneca	17	Initial number infected	2
Number doctors	5	Restock-pfizer	41	Initial-central-vaccine-stock	70	Replications	1
Injection-capacity-doctors	2	Restock-moderna	17	Number groups	10		

Reference parameter setting

The reference parameter setting is shown in the Table 19. Variations on these variables are presented in chapter 4.

Table 19: Reference parameter setting scaled model

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
Number-patients	1395	Probability-delay	0	Social influence	2	Safety-waiting-time	5
Number doctors	5	Restock-pfizer	41	Influence service	10	Delivery-time	24
Injection-capacity-doctors	2	Restock-moderna	17	Influence waiting time	2	Percentage anti-vaxxer	14
Initial-central-vaccine-stock	70	Restock-astrazeneca	17	Number-groups	10	Influence anti-vaxxer	3
Initial-number-infected	2	Virus-spread-chance	15				