HEALTH BEHAVIOUR THEORIES AND THE NORWEGIAN RESPONSE TO COVID-19

A SYSTEM DYNAMICS MODELING APPROACH

THESIS SUBMITTED IN PARTIAL FULLFILMENT OF THE REQUIRMENTS FOR MPHIL IN SYSTEM DYNAMICS FRA UNIVERSITET I BERGEN

CHRISTINA GKINI (276279)

SUPERVISED BY: PÅL I. DAVIDSEN,
Faculty of Social Sciences, University of Bergen

UNIVERSITETET I BERGEN
Det samfunnsvitenskapelige fakultet

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Abstract

The aim of this work is to investigate the coupled dynamics between infection and behavioural response at the population level in the case of the novel Coronavirus 2019 (COVID-19) in Norway. For this purpose, a System Dynamics simulation model has been developed that proposes a number of modifications on classical differential equations epidemiological models to better apply in the case of COVID-19. Moreover, this work attempts to bring together well-establish theories under the umbrella term Health Behaviour Theories that investigate the response of individuals to environmental threats to their well-being. We have tested both components of the model in isolation and combination and were able to replicate, with a sufficient degree of accuracy and under logical assumptions, the observations of the spread of COVID-19 in the country. More importantly, we have developed a simulation model that captures numerous of the common elements identified in Health Behaviour Theories in one composite structure that can allow for experimentation with various assumptions.

Our model highlights the importance of communication strategies in the management of environmental Threats and, in line with known theories, suggests that it is optimal to share messages that not only highlight the significance of the Threat, but also emphasise the Efficacy of a proposed behavioural response in mitigating it. Communication is important but we need to ensure that we minimize and understand the Costs associated with any proposed measure. Despite limitations in our work that do not allow us to propose specific policies for the management of COVID-19, our model suggest caution with “return-to-normal” scenarios.

This work has provided support for the attempt to develop a common theoretical framework of peoples’ response to threats and provided with important focal points for further iterations. Those are considered significance due to their possible applications beyond COVID-19, both in other epidemiological contexts and health-related decision making, but also in the general understanding of peoples’ reaction to environmental Threats to their wellbeing.

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Chapter 1: Introduction

> When a social contagion is coupled to a biological contagion, the resulting disease-behaviour system can exhibit dynamics that do not occur when the two subsystems are uncoupled and in isolation from one another. This illustrates the lesson of complexity science that the whole is more than the sum of the parts.
>
> (Bauch & Galvani, 2013, p. 47)

The Coronavirus Disease 2019 (COVID-19)

In late December 2019, reports emerged about cases of pneumonia of unknown origin in Wuhan, China (World Health Organization, 2020a). The pneumonia was described as caused by a new coronavirus, later named the Coronavirus Disease 2019 (COVID-19) (Wu et al., 2020) which, due to its high infection potential among other factors, soon started spreading throughout the world. COVID-19 was declared a Public Health Emergency of International Concern (PHEIC) by the World Health Organization the 30th of January 2020 (World Health Organization, 2020c) and was later characterized as a pandemic on the 11th of March (World Health Organization, 2020d).

As of May 28th, 2020, there have been 5,593,631 reported cases globally (World Health Organization, 2020b), although the actual numbers of infected cases could be much higher. The death count of the disease has reached 353,334 (World Health Organization, 2020b) and many more people have been hospitalised in critical condition. The impact of the virus at a global level is undeniable (see Figure 1) and almost all countries in the world have had been affected by COVID-19 directly (AL JAZEERA NEWS, 2020) and definitely all indirectly through the financial consequences of the disease. In many countries, the death toll has been very high as COVID-19 has significantly strained public health systems, global supply chains, and research capacities. COVID-19 has led to enormous disruptions in economy and peoples' daily lives, and the socio-economic impact of the pandemic is undeniable (United Nations Development Programme, 2020)

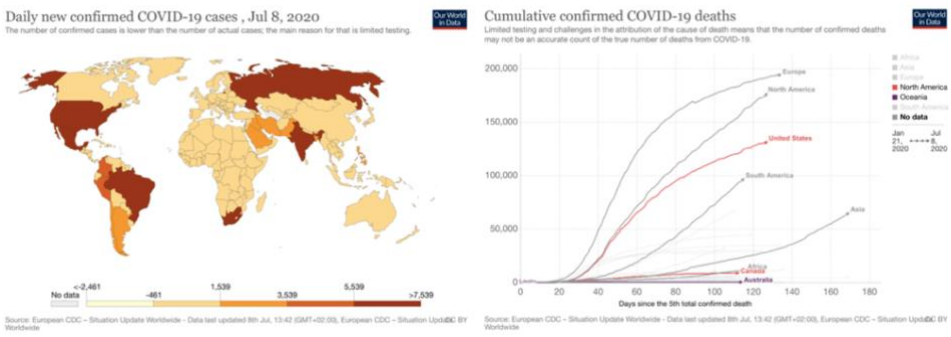


Figure 1: Daily new Confirmed COVID-19 cases and Cumulative deaths, July 8, 2020. (European Centre for Disease Prevention and Control, 2020; in Roser, Ritchie, Ortiz-Ospina, & Hasell, 2020)

The severity of COVID-19 has led to an unprecedented response at both the global and local level and by actors at the highest and lowest "influence" spheres: from global institutions and organisations, governments, the scientific community, to each individual. Indeed, this "natural experiment" (Sibony, 2020) has highlighted the significance of the interplay between the different actors at all levels of influence in the effort to "flatten the curve". Governmental responses include but are not limited to testing policies and adjustments of the health care system's capacity for testing and treatment, quarantine and lockdown decisions, communication of the prevalence and severity of the virus, etc. Those responses have to a large extent been informed and supplemented by the information provided through the response of the scientific community. Computational epidemiological modelling in particular has proven crucial in providing evidence on how to respond to the pandemic, both by offering guidance and assistance to governments to decide on and implement efficient policies and by helping engage the public.

A very important insight of the global experience with COVID-19 has been the significance of actions of individuals, aggregated to the population level. *Social distancing* is a term that became globally known and that refers to "any non-pharmaceutical intervention, taken by individuals or by policy makers, which acts to decrease the contact rate between infected and susceptible individuals" (Toxvaerd, 2020, p. 1). *Self-isolation* denotes the voluntary decision by individual agents to maintain "*physical separation* by reducing the number of times people come into close contact with each other across whole populations" (Bonell et al., 2020, p. 1) and is thus different from quarantine or isolation of diagnosed or suspected carriers of the disease. Moreover, in the case of a transmissible disease, *other hygienic measures* can have a large effect on transmissibility. Hand washing, maintaining proper distance, protective coughing and masks, all have been emphasised as significant measures to reduce infections (e.g. Khetrapal Singh, 2020; Norwegian Institute of Public Health - FHI, 2020d). Compliance with the above measures and all other "sacrifices" of individuals have proven one of the most important resources in fighting the pandemic and this knowledge leads to the understanding that "the stakes have never been so high when it comes to incorporating behavioural insights into policy design" (Sibony, 2020, p. 353). Social and Behavioural Sciences are valuable resources as they can provide insights and support to our efforts to combat COVID-19, as well as learn from it. The topics that are relevant in studying the human response to the pandemic as well as its effects on individuals are many and can be applied at various stages of the COVID-19 timeline (see Figure 2).

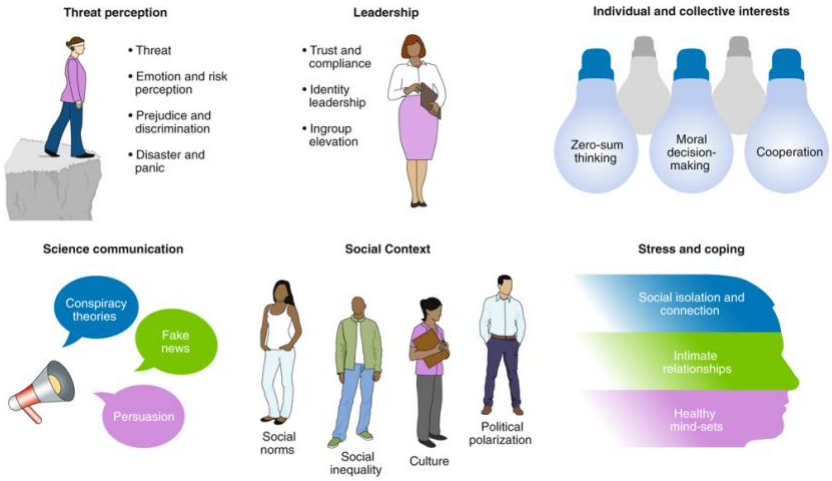


Figure 2: Some relevant for COVID-19 topics from social and behavioural sciences (infographic by van Bavel et al., 2020, fig. 1)

In this project, we will focus on the initial response of the population to Covid-19 and how the perception of the Threat that the virus poses to an individual's wellbeing might lead them to follow advice and proposed measures that can act to mitigate this environmental Threat. There have been numerous studies using computation approaches in order to investigate individuals' responses to epidemics, as we will see in more detail in Chapter 3, however, most such models focus only on information regarding the prevalence of the disease (termed usually "prevalence-elastic response" (Funk, Salathé, & Jansen, 2010, p. 1247)). Such approaches, while very valuable, have been criticised as treating individuals as "Homo EconomSickus" (Epstein, Parker, Cummings, & Hammond, 2008, p. 1): fully rational agents making decisions under some hypothesised (or optimised) utility function and/or under perfect information. An alternative approach to studying the response of the population comes from the Psychological field and well-established Health Behaviour Theories that have a long tradition in studying health-related decision making or, more generally, peoples' response to environmental threats, particularly pertaining to one's wellbeing (see, for example Glanz, Rimer, & Viswanath, 2008; Redding, Rossi, Rossi, Velicer, & Prochaska, 2000). Attempting to couple the two traditions, Computational Models and Health Behaviour Theories can, we believe can be a valuable approach to understanding the phenomenon at-hand.

The response and effectiveness of different governmental policies and individual decision-making in the case of COVID-19 offer public officials and researchers valuable lessons on best responses under global crises. For the one currently underway, despite the success that can be observed in many of the cases, the "fight" does not seem to be over; development of vaccines is a slow and uncertain process, mutations of the virus can easily bring new waves of a similarly or more deadly disease, and in such an interconnected world, even 1 undetected infection can threaten the stability we have managed to achieve. But this crisis also provides us with the opportunity to explore and, hopefully,

gain understanding of how we can optimally responses to future crises, both at the level of policy making and communication, as well as individually. This work hopes to assist in this effort.

Research Objective & Research Questions

In this project, we aim to contribute to the tremendous response of the global scientific community with a simulation model emphasizing the coupling between viral dynamics and the behavioural response of the population. For this, we develop a model that builds upon classic epidemiological models in a way that we believe better describes COVID-19 and we apply this structure in the case of Norway to assess its validity. While Norway can be considered one of the "success stories" in the fight of COVID-19, the virus did penetrate the society causing serious health and socioeconomical disruptions (see Figure 3)

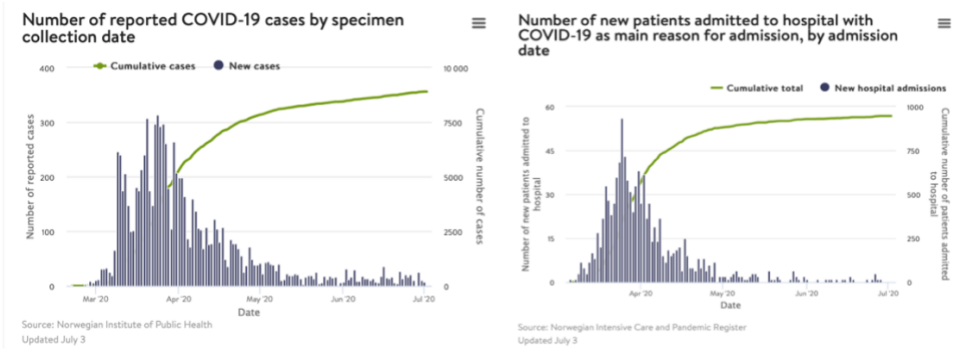


Figure 3: Number of reported COVID-19 cases per specimen collection date & Number of new patients admitted to hospital with COVID-19 as the main reason for admission. Source: Norwegian Institute of Public Health – FHI (2020c)

Regarding the behavioural response of the Norwegian population, we will attempt to bring together insights from earlier computational models as well as psychological theories described under the umbrella term *Health Behaviour Theories*. Our aim is to combine theoretical insights into a compound theoretical construct which we will build and test via a simulation model. With this, we aspire to provide an endogenous view of peoples' response to the threat posed by COVID-19 and begin exploring what decisions, at the governmental and individual level, can facilitate responses that can assist in mitigating that threat.

Research Questions

1. Can well-known models of infectious disease be adopted for the case of COVID-19?
    a. Could accounting for gradual progression among stages of the disease accurately describe the reality of Covid-19?
    b. Can such a model offer us additional information?

c. Could such a model be utilised for other viruses or diseases?

2. Is the behavioural response of the population, in terms of compliance with proposed behavioural measures, significant for the prevalence of Covid-19 in the population?
    a. If so, is it sufficient that this response is grounded in information on the prevalence of the disease?
    b. Are there additional mechanisms that can be utilised to enhance compliance with proposed behavioural measures?
        a. More specifically, are communication messages important in helping mobilise the desired response?
        b. can targeted information regarding the effectiveness of the proposed measures have a significant impact?

3. Can existing theoretical frameworks of decision making in response to environmental threats to our wellbeing be combined in a unified framework?
    a. Can they be translated and represented in a dynamic, computational model and, if so, is System Dynamics an appropriate method?
    b. Is such a framework relevant only for the COVID-19 pandemic?

Methodology

To examine those questions, we will develop a simulation model to represent the spread of COVID-19 in Norway and allow us to test the endogenous behavioural response. The approach we will follow is represented in the following sections

Simulation Modeling

As already briefly discussed, simulation modelling has had a main influence in the response to CCOVIDovid-19 at a global level. This is to be expected as "[…] when experimentation in real systems is infeasible, simulation becomes the main, and perhaps the only, way you can discover for yourself how complex systems work" (Sterman, 2000, p. 38). In this study, we will develop a computation model using the System Dynamics (SD) modelling method to explore the dynamics of the spread of COVID-19. SD is a simulation method that applies to complex, dynamic problems and it involves dynamic definition of those problems (as they develop over time) and an endogenous view focusing on the complex feedback between elements of the system. Those elements are represented as levels and rates (or stocks and flows), and are explored as continuous quantities (Forrester, 1961; Richardson, 2011). SD is "an iterative and interdisciplinary process, which views problems holistically" (Palmer, 2017, p. 2) and, as such, lends itself well to a complex, interconnected problem such as COVID-19 (for a more extended discussion on SD modeling for the case of Covid-19, see Currie et al., 2020).

Moreover, the SD method has a long tradition of applications to Public Health (for a brief review, see Homer & Hirsch, 2006) and has already been utilised successfully in the case of COVID-19 (for example, Homer, 2020; Pruyt & PEAS CENTER, 2020; Struben, 2020). Decision-making, in general, has been at the core of the methodology since its inception (see, for example Forrester, 1987) and SD modeling has been applied widely to investigate responses to environmental situations at the individual or aggregate level (e.g. Batchelder, Gonzalez, Palma, Schoenbaum, & Lounsbury, 2015; Hirsch, Levine, & Miller, 2016; Jacobsen & Bronson, 1987).

Not least, SD has been developed and grown as an applied method, focused largely on policy design and testing but it also has and will continue to be successfully used for the development and testing of theoretical insights (de Gooyert, 2019; De Gooyert, 2016; de Gooyert & Größler, 2018). Since our work is situated somewhere in the middle of this continuum between application and theory, the methodology fits our purpose.

Specific Approach

The approach we use combines elements of Phenomenon driven explanation (de Gooyert, 2019) and Grounded Theory (see, for example Chun Tie, Birks, & Francis, 2019).

With a *Phenomenon-Driven Explanation* process, the researcher begins with a phenomenon for which they "develop a simulation model as a 'dynamic hypothesis', a potential explanation of the phenomenon by proposing the structure, in terms of causal relations, that drives the behaviour" (de Gooyert, 2019). The simulation model is validated through its ability to replicate the reference mode of behaviour and, if valid, "what-if" scenarios can be tested to develop new insights on the phenomenon.

Grounded Theory is a method "that focuses on creating conceptual frameworks or theories through building inductive analysis from the data" (Charmaz, 2006, p. 187). In this framework, a researcher "begins with an area of study and allows the theory to emerge from the data" (Corbin & Strauss, 2014, p. 12). This emergence of theory from the data is possible as the researcher "links" concepts and insights together, and as Luna-Reyes & Andersen suggest "since 'linking' is at the heart of SD, grounded theory speaks to the same goal of drawing relationships among factors in a targeted system" (2003, p. 284). We find the multi-grounded theory framework proposed by Goldkuhl & Cronholm (2003) to be very insightful in adding the process of *Theoretical Grounding* in addition to *Empirical* and *Internal Grounding* (see Figure 4). Theoretical Grounding refers to the process whereby the emerging theory is contrasted with established theories representing the same phenomenon in order to provide validation of the proposed structure.

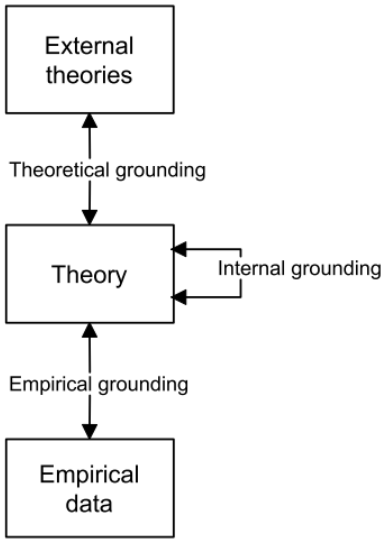


Figure 4: The three complementary grounding processes proposed by Goldkuhl & Cronholm (2003)

Data Collection

The data required to build and validate the model to test our hypotheses can be broadly categorised in two categories:

- Epidemiological Data: data on the characteristics of the viral agent (e.g. relative infectivity, duration of infection, severity proportions), as well its spread in Norway (e.g. number of infected that have been hospitalised, in critical care, tested).
- Health Behaviour Data: data of usually more "soft" nature on how individuals respond to environmental threats or make health-related decisions. Established theories and studies under those theories, as well as mathematical models of response of the population to an epidemic fall under this category

A more detailed view of specific data sources utilised in this research with relevant examples, as well as the method of collection of the data and their contribution to the simulation model can be found in Table 1.

Table 1: Data Sources, Collection, and their Contribution

Source Type	**Examples**	**Collection**	**Contribution**
Epidemiological numerical data	Characteristics of viral agent (Ferretti et al., 2020; Gaythorpe et al., 2020; Gudbjartsson et al., 2020; He et al., 2020; The WHO-China Joint Mission on Coronavirus Disease 2019, 2020); Prevalence of the virus in Norway	Literature Review with focus on information about the viral agent. Peer-reviewed papers were prioritised but, due to the circumstances around COVID-19, preprints were included in the review. Norway-specific data from	Parameter estimation, validation

	(Norwegian Institute of Public Health - FHI, 2020c, 2020b)	the Norwegian Health Authorities were prioritised	
Existing Simulation Models of COVID-19 (epidemiological)	SD Models (Homer, 2020; ISEE Systems, 2020; Struben, 2020 etc.); Other Simulation Models, e.g. (Ferguson et al., 2020; Norwegian Institute of Public Health - FHI, 2020a; NTNU COVID-19 Taskforce, 2020)	Review of published models with documentation of assumptions regarding structure and parameter values. SD models both published and informally peer-reviewed and published in the SD Society's COVID-19 resource page[1]	Causal structure, equations, parameter estimation
Mathematical / Computational Models of Behavioural responses to epidemics	(Funk, Gilad, Watkins, & Jansen, 2009; Funk, Salathé, et al., 2010; Liao & You, 2014; Poletti, Caprile, Ajelli, Pugliese, & Merler, 2009; Reluga, 2010; Toxvaerd, 2020)	Review of published mathematical and computational models focusing on structural understanding of population-wide responses to epidemics.	Causal structure
Documented Qualitative Data	Health Behaviour Theories and Models (e.g. Champion & Skinner, 2008; M. Conner & Norman, 2005; Glanz et al., 2008; Madden, Ellen, & Ajzen, 1992; Norman, Boer, & Seydel, 2005; Weinstein, 1993; Witte, 1992)	Literature Review focusing on the structural understanding of the behavioural response of the population to environmental threats or, more broadly, health-related decision-making	Causal structure, parameter estimation

Ethics

This work did not involve primary data collection and, as such, ethical considerations regarding the treatment of research participants are not applicable. However, every modelling attempt needs to be ethically evaluated as "[t]he consequences of the use of a model are morally relevant" (Diekmann, 2011). Some of the identified principles for such an evaluation are presented here.

Integrity represents the modeler's obligation to follow professional standards. Modelers need to act "in an ethical manner as they apply the generally accepted best practices of their profession" (Walker, 2009, p. 1051). Best-practices of our field have been employed in the development, testing, and documentation of our model according to long-standing guidelines in our field (e.g. Barlas, 1996; Martinez-Moyano & Richardson, 2013; Rahmandad & Sterman, 2012; Sterman, 2000)

[1] Available at https://www.systemdynamics.org/covid-19

Transparency refers to clear stating of assumptions, an understandable model design, and explicit explanation of its applications and restrictions (Diekmann, 2011). SD models inherently call for transparency of assumptions as they are causal-descriptive, and as such, "white-box" models (Duggan, 2016, p. 123). In contrast to "black-box" models, where the internal workings of the model are not explicitly known, white-box models call for explanation of each causal link and assumption (Barlas, 1996, pp. 185–186). Detailed descriptions for each part of the model are presented in the relevant sections and an explicit documentation following the standards proposed by Rahmandad & Sterman (2012) can be found in Appendix. In terms of an "understandable design", we have attempted throughout the development of the model, with a degree of success to be judged by the reader, to utilise terminology that is known or commonly utilised, directionality of variables that might be more intuitive and fitting to the terms, and disaggregate variables to assist in the understanding of the equations.

It is important to note that, in simulation modelling approaches, "[t]ransparency depends on the ethical behavior of the modeler, though it is the model itself that is ethically charged" (Palmer, 2017, p. 3). The modeler, besides adhering to research ethics of general conduct, has to answer additional ethical questions, as for example:

> "Who matters? What matters? What time horizon matters? What are the boundaries of the system/model to be considered? For many system dynamicist, the criterion determining whether an element or a structure is modelled or not –and hence where the boundary lies–, is whether the inclusion/exclusion changes the behaviour of the model, which is a technical criterion. But these questions are essentially ethical questions"
>
> (Pruyt & Kwakkel, 2007, p. 4)

The above has been a consideration of ours, especially working on a topic that has so serious implications for everyone and, perhaps even more so, since our focus is on the behaviour of individuals. The "Who matters" question has been particularly difficult to answer and, as further described at later sectors, we have decided on including a mechanism of direct communication between people (which we will refer to as the "bottom-up" mechanism). Many decisions regarding this mechanism, heavily influenced by lack of data and parameter uncertainty, have perhaps led us to underestimate its importance in the behaviour produced by the model. As such, its exclusion would not "change the behaviour of the model" sufficiently and, if anything, would make things easier. The eventual decision to maintain it, and try to understand its value, was an ethical one.

In terms of Transparency of the applications and limitations of the model itself, it is firstly significant to state that our model's purpose, according to the classification proposed by Mayer, Van Daalen, & Bots (2004), is to "research and analyse", that is, to produce knowledge in a specific domain. This knowledge might be relevant to policy, however "the translation of the results of their research into a policy design or recommendation is not a major part of the purpose" (Walker, 2009, p. 1052).

While the model is aimed to explore policy options for a current high-stakes problem, its main purpose is *not* to suggest specific policies. Significant limitations and uncertainties in both parameter values and structural components of the model, as well as lack of field-specific knowledge of the modeler, limit its ability to be used as a policy recommendation tool at its current iteration. It is crucial to remember that "Mathematical models are a great way to explore questions. They are also a dangerous way to assert answers" (Saltelli et al., 2020, p. 484). We have remained conscious of this fact during the development of the model and, hopefully, in its presentation hereafter.

Chapter 2: Modelling the Virus

The most common model of infectious diseases forming the basis of almost all the disease models studies since its inception is the SIR (Susceptible – Infected – Recovered) model (Kermack & McKendrick, 1927). In this model, the total population is divided in three categories, or three main stocks:

1. Susceptible (S): The population which has not been infected by the disease but can be infected upon contact with an infectious person.
2. Infected (I): The population currently infected with the disease
3. Recovered (R): The population which has contracted the disease and recovered (most commonly being immune to further re-infection)

The SEIR model was later developed to account for what is known as the latency period: the period a person is exposed to the disease but not infectious. The class of Exposed individuals (E) is the only addition to this model. The system is described as a set of differential equations:

$$\frac{dS}{dt} = -\frac{\beta IS}{N}$$
$$\frac{dE}{dt} = \frac{\beta IS}{N} - \sigma E$$
$$\frac{dI}{dt} = \sigma E - \gamma I$$
$$\frac{dR}{dt} = \gamma I$$

where N represents the total population, $1/\sigma$ is the average duration of incubation, and $1/\gamma$ the average duration of infection. The probability of transmission between a susceptible and an infected person β is «the product of the per capita contact rate and the probability of infection after contact with an infected individual» (Radulescu & Cavanagh, 2020, p. 3). It can therefore also be represented as:

$$\beta = kb$$

where k represents the average contacts per person daily (or contact rate) and b the infectivity per contact (Xiong & Yan, 2020). In this way, the equation of the infection rate becomes:

$$\frac{\beta IS}{N} = \frac{kIS\beta}{N}$$

This formulation is significant as it highlights the element that has been mostly utilized in the attempts to control the pandemic: the contact rate k. As evident from the above equations, the system is very sensitive to (or largely determined indeed by) this parameter.

A number of modifications to the classic SEIR model of disease dynamics were proposed by Pål I. Davidsen, for its application in the case of COVID-19. Those include a gradual progression towards more severe symptomatology, a breaking of the, common to classic SEIR models, "perfect-mixing" rule with the introduction of high order delays in the symptom progression, and a structure that allows us to "track" the number of people at any particular day of their disease. Those modifications will be presented in more detail in the following section.

Modifications of the Classic Model

Severity Status

A usual categorisation of the severity status of COVID patients is in cases that are mild, moderate, severe, or critical (see, for example Pan et al., 2020). This differentiation between different severity categories is important for numerous reasons:

i. It can help us best determine the strain on Health institutions (hospital beds, ventilators, etc.) as well as the number of deaths from the disease.
ii. Testing Capacity in most countries had not been sufficient to test all persons reporting with symptoms that could be attributed to COVID-19. A common practice has been to prioritise testing in more severe cases. Differentiating between severity categories allows us both to make better estimates of the true number of infected and determine how prioritised testing decisions can be considered .
iii. While much still remains unknown, there are indications that different severity categories might also have different disease characteristics, from disease duration to viral loads and, most importantly, infectivity (e.g. Byambasuren et al., 2020)
iv. Not least, different symptoms can lead to different behavioural tendencies: the more severe the symptoms, the more likely it is that people will isolate or be quarantined (voluntarily or mandatory). Population not experiencing any symptoms, even if they carry the disease, are expected to make the same decision regarding isolation as the general population.

Gradual Progression across Severity Categories

Besides the disaggregation of the infected population across severity categories which has been relatively common in modelling attempts of COVID-19 due to its significance, we account for a gradual progression towards more severe symptoms and eventual hospitalization or need for critical care. Unlike other early-response SD models which disaggregate infected persons across severity categories

as soon as they enter the infectious period of the disease (Fiddaman, 2020; ISEE Systems, 2020), we conceptualise the development of more severe symptoms as a gradual process, a progression through all the previous severity stages. As an example, an individual who has died after spending time in critical care, has gradually progressed from no symptoms, to more and more severe symptoms, hospitalization, and some time in critical care before dying. While the average stay in all the previous stages is lower than that of a patient not reaching a critical care requiring severity, there is *some* time spent in all those stages.

Moreover, in many of the proposed models, we observe what is termed as the "perfect mixing rule": formulating the movement between the different stocks as a first-order delay where material leaves the stock over some average delay time D. In this way, we allow each item the same probability to exit the stock, independently of its arrival time. This perfect-mixing does not fit well, in our opinion, with the dynamics of COVID-19 as the probability of movement to more severe stages of the disease has some dependency on the arrival time. A common way to break this rule is the introduction of higher order delays where "the higher the order of the delay, the less mixing and the smaller the variance of the output" (Sterman, 2000, p. 420). We conceptualise here the movement between the severity categories to be best represented by a third-order delay, represented as three distinct stages at each severity level.

We believe both those mechanisms to increase the capacity of the model to fit the reference behaviour, especially for those Infected who will eventually develop more severe symptomatology.

Tracking individuals based on day of illness

The structure we propose utilises Conveyor Stocks to "keep track" of individuals at different days of their infection. A Conveyor, akin to a conveyor belt, allows material within it to move progressively (at every DT) across the conveyor's "slats" (for more information, see ISEE Systems, n.d.). As such, it can provide us with the exact number of material (here, infected people) that has entered the conveyor at some previous point in time or information on how long it has been within the conveyor. This type of information is significant for various reasons:

i. The discrete nature of Conveyors ensures that individuals characteristics are maintained as they would in reality (a person in the fifth day of Infection has passed discretely four days as Infected), and those can be utilised to better understand movements of individuals according to such characteristics.
ii. The structure can help us clearly associate different characteristics that seem to change across days of the disease (viral load, relative infectiousness, testing efficiency, etc.). While there are other methods in the SD toolbox to do so (we are refering to co-flow structures. For a discussion, see Gambardella, Polk, Lounsbury, & Levine, 2017), we find such associations via conveyors to be easier to formulate and, perhaps, easier to communicate.

iii. It allows for a more "individual-based" view of the disease progression that can improve the communication potential of the infectivity model.

Main Infection Model (SEIR)

As described above, the model is a modified version of the classic SEIR model accounting for a gradual disease progression through a number of stages and days of infection. The main stocks are the *Susceptible population* (S), the *Exposed Non Contagious* population, the Infected population at each severity category (*Asymptomatic Infected AI, Symptomatic Infected SI, Hospitalised Infected HI, and Critical Care Infected CCI*) and at each stage in their severity category (e.g. Asymptomatic Infected at first stage *AI*, Asymptomatic Infected at second stage *AI s2*, and Asymptomatic Infected at third stage *AI s3*). The *Recovered* and *Dead* stocks are also disaggregated according to the severity category the individual recovered from or died from respectively: for example, a person recovering as Hospitalised Infected will be moved into the respective Hospitalised Infected Recovered stock (*HI Recent Recovered*) at the same "day slot" they were occupying when they recovered. The *Recent Recovered* and *Recent Dead* conveyors hold recovered individuals for 45 days (the Transit Time) since those entered the infection chain as Asymptomatic Infected (that is, through the *becoming infectious rate* or the *importation rate*). After this period, the *Recovered* and *Dead* stocks keep track of the long-term recovered and dead population. The same stocks are replicated for the *Tested Infected* across severity categories and stages within each category (see Figure 5).

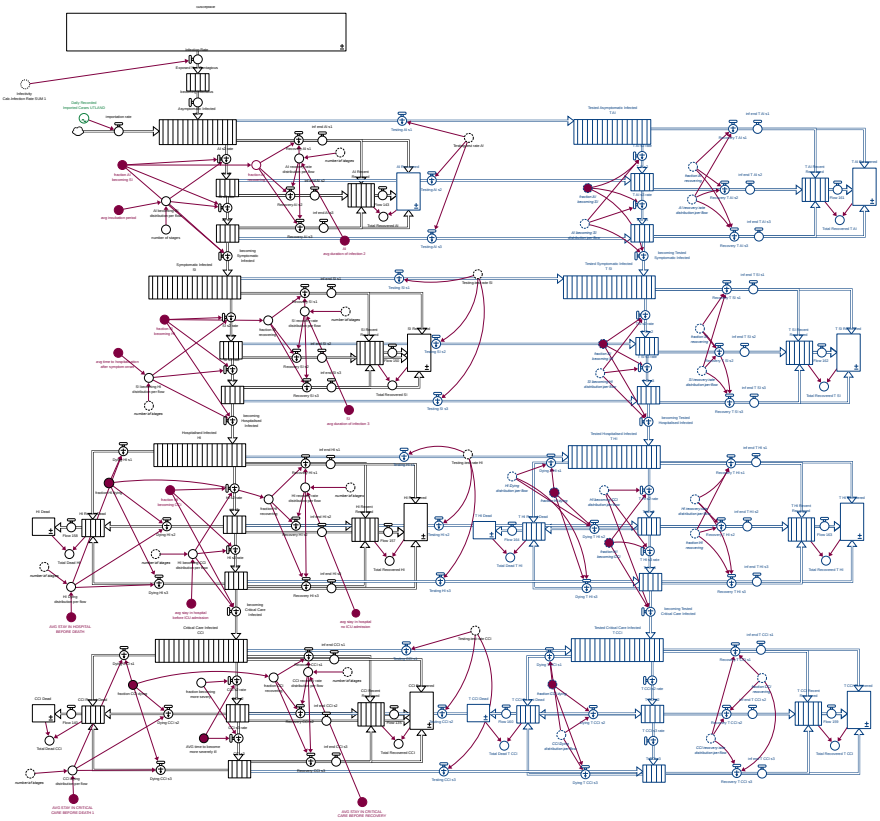


Figure 5: Top-Level View of the main Infection Model. In black are the stocks for the non-tested Infected, in blue those for the Tested Infected & purple variables represent parameters

A *Susceptible* person (S) can become *Exposed* to COVID-19 (E) upon contact with any *Infectious* person (I_{total}). Initially, Infected cases are imported from abroad and data estimates on imported cases (Norwegian Institute of Public Health - FHI, 2020c) are used to initiate the spread of infection in Norway. We assume an additional 40% imported cases than those reported, which is in line with estimates on the proportion of Asymptomatic Infected (see Table 2 below). Those imported cases are assumed to be entering the infection chain at the Asymptomatic stage through the *importation rate*.

Exposed individuals remain Non-Contagious for a period of 2 days, which represents the latency period of the virus (Tuite, Fisman, & Greer, 2020). After this period, they become contagious and move to stock of *Asymptomatic Infected AI*. An Asymptomatic Infected person at this first stage can either move to *Asymptomatic Stage 2* or recover as Asymptomatic (move to the stock *AI Recent Recovered* and then to the "long-term" *AI Recovered* stock). An *Asymptomatic Stage 2* can, again, either move to *Asymptomatic Stage 3* or recover as Asymptomatic and so on. In this way, a fraction of those Infected will progress to develop symptoms (*become Symptomatic*), while some will recover as Asymptomatic, from either of the three stages. *Symptomatic Infected SI* follow the same journey, either towards recovery or towards gradually more severe stages, with a fraction eventually becoming *Hospitalised Infected HI*. As individuals enter the severity stage of Hospitalised Infected, the risk of mortality due to the disease presents itself. Hospitalised Infected can therefore, as before, recover or move towards more severe stages but can also die due to COVID-19 from either of the three stages.

Individuals would in this case be moved through the *dying* rate of their stage to the *HI Recent Dead* and, eventually, the *HI Dead* stocks. The final, most severe stage is that of *Critical Care Infected CCI* – individuals requiring intensive care due to complications of their infection. The mortality risk in this case is higher and Critical Care Infected either recover or die from each of the three severity stages[2].

The structure described above is duplicated as is for the *Tested Infected* across all severity categories and stages. Infected individuals at each stage can get tested through the respective testing rate of their stage and be moved at the Tested structure, at exactly the same position (both in terms of severity and stage and at the same "day-slot") they were holding in the Non-Tested / original structure. As Tested, they progress through the same subsequent stages or recover in exactly the same way they would as non-tested. For a more focused view of the progress from infection until the first stage of Symptomatic Infected, see Figure 6

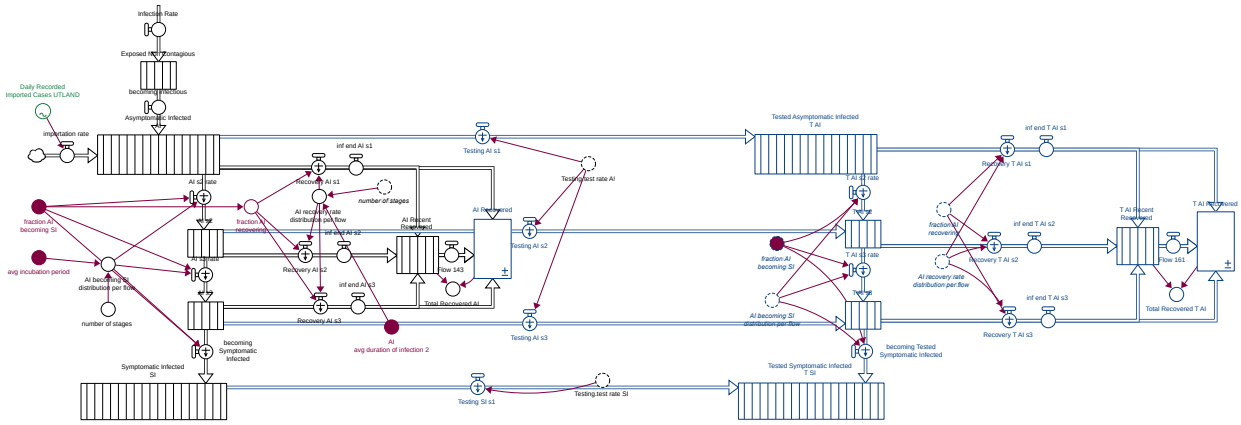


Figure 6: Partial View of the Infection model. The three stages that an Asymptomatic Infected needs to go through before becoming Symptomatic are similar at each of the severity categories. The lighter blue structure on the right represents the Tested infected

Main Assumptions of Infectivity Model

Asymptomatic Infections / Proportion of severity categories

The fraction of Asymptomatic Infections remains one of the major uncertainties regarding COVID-19. There is a significant distinction between those who remain Asymptomatic throughout the entire infection period of the infection, and those who develop symptoms at later stages of their progression. Unfortunately, many of the studies do not use a longitudinal approach that would allow us to estimate the fraction who is, at the time of the study, and *remains* Asymptomatic.. Due to symptom-based screening, especially at initial stages of the epidemic, the possibility of variations of the Symptomatic proportions due to age, as well as the previously mentioned non-longitudinal data,

[2] In this model, there is no consideration of movement of individuals "back" in previous stages: an infected person that is in Critical Care is not returning to Hospitalised

estimates of Asymptomatic cases vary significantly from 5% to 80% (for a quick review, see Heneghan, Brassey, & Jefferson, 2020).

Interestingly, modelling studies report on average higher fractions of Asymptomatic infections (Buitrago-Garcia et al., 2020). The Imperial College modelling team estimates that "two-thirds of cases are sufficiently symptomatic to self-isolate (if required by policy) within 1 day of symptom onset" (Ferguson et al., 2020, p. 5) but the most usual estimate for the Asymptomatic proportion seems to be 40% (Ferretti et al., 2020; Gudbjartsson et al., 2020). The model developed by the Norwegian Institute of Public Health (2020a) uses the same assumption, while a similar model developed by the Norwegian University of Science and Technology (NTNU) assumes that 50% of those exposed will actually develop symptoms (2020) (for a more detailed view, see Table XXX).

Reported data from over 72.000 cases in China, estimate 81% of cases as mild, 14% as severe, and 5% as critical (The Novel Coronavirus Pneumonia Emergency Response Epidemiology Team, 2020), although those estimates might underrepresent mild cases as only 1,2% of the analysed patients were identified as Asymptomatic. Similar data for China have been reported by the World Health Organisation (The WHO-China Joint Mission on Coronavirus Disease 2019, 2020). Table 2 presents the values used for the relative fraction of infected at each severity category as well as evidence from the relevant literature.

Table 2: Proportions of Infected at each of the severity categories: chosen parameter values and values identified in the literature either as estimates or as parameters used for Models of Covid-19

Proportion Asymptomatic = 45%		
Estimates	17,9%	(Mizumoto, Kagaya, Zarebski, & Chowell, 2020)
	1/3	(Arima et al., 2020)
	43%*	(Gudbjartsson et al., 2020)
	56%*	(Arons et al., 2020)
	87,9	(Sutton, Fuchs, D'Alton, & Goffman, 2020)
Model Assumptions	1/3	(Ferguson et al., 2020)
	40%	(Norwegian Institute of Public Health - FHI, 2020a)
	50%	(NTNU COVID-19 Taskforce, 2020)
	40%	(Ferretti et al., 2020)
*reported at the time of study: some might develop symptoms later		
Fraction Symptomatic Infected becoming Hospitalised Infected = 40% of Symptomatic (accounting for 22% of all Infected)		
Estimates	13,8%*	(The WHO-China Joint Mission on Coronavirus Disease 2019, 2020)
	17%*	(Gaythorpe et al., 2020)
Model Assumptions	Varied according to age	(Norwegian Institute of Public Health - FHI, 2020a); (NTNU COVID-19 Taskforce, 2020)

	16%	(Homer, 2020)
*of total Infected		
Fraction Hospitalised Infected entering Critical Care = 45% (accounting for 11% of all Infected)		
Estimates	6,1%*	(The WHO-China Joint Mission on Coronavirus Disease 2019, 2020)
Model Assumptions	30%	(NTNU COVID-19 Taskforce, 2020); (Ferguson et al., 2020)
	26%	(Tuite et al., 2020 based on estimates by Wang et al., 2020)
*of total Infected		

It is significant to note that all fractions were calibrated and the discrepancies observed between our estimates and those described in other models are expected due to the structure we have developed. For example, Asymptomatic Infected are not "separated" from the other severity categories after infection at an Asymptomatic stock from which they can only recover. Instead, the continue "leaking" to the Symptomatic stock until their recovery.

Latency Period and Symptom Progression

The term latency period is used to describe the time from infection to the beginning of infectiousness while the incubation period refers to the average time between infection and onset of symptoms (see Figure 7). The duration of the latent period is a significant while uncertain factor (for a more detailed discussion, see Sadun, 2020). If individuals become infectious immediately or shortly after their infection, the reproduction number will be higher as they can immediately infect others around them. Assuming the same incubation period, a higher latency period would tighten the "window" for infecting others prior to realizing that one might be infected. Reported values for the latency period are 2.56 (with ST DEV 0,72, Peirlinck, Linka, Sahli Costabal, & Kuhl, 2020) and usual parameter values used range between 1 and 3 days (Bi et al., 2020, see also Table 3)

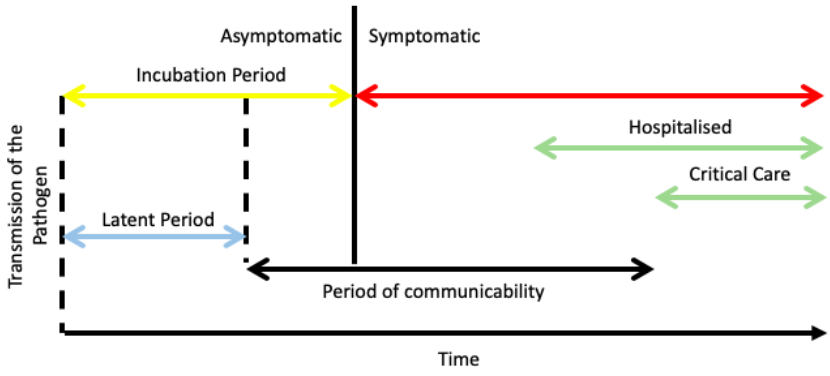


Figure 7: Key time period of COVID-19 infection. Adapted by Z. Liu, Magal, Seydi, & Webb (2020) with the incorporation of Hospitalised and Critical Care periods

Uncertainty around the latency period of the disease's and the relevant time of progression to more severe symptomatology is still rather high. Differences in age, prior health, capacity of health systems, and the overall uncertainty regarding *when* an individual got the infection, lead to large variations of reported values. Moreover, very common estimates of those parameters from modeling studies are heavily structure dependent. In our model, we introduce additional, high order delays in the progression between severity stages, so some deviation is to be expected. In Table 3, we present the values used for the average time individuals spent at each severity stage or recover / die together with estimates from the relevant literature or assumptions from modeling approaches.

Table 3: Durations of residence at different stages across all severity categories: chosen parameter values and values described in the literature

Asymptomatic & Symptomatic Infected		
Average Duration of Infection for Asymptomatic Infected = 20[1] Average Duration of Infection for Symptomatic Infected = 16 (with 4 days average incubation period – time from infection to becoming Symptomatic)[1]		
Estimates	20,8	(Bi et al., 2020)
1. We need to note that this is not the same as the duration of infectivity (see Infectivity Module section below) and hence this parameter is used to mainly give us information about the number of people experiencing symptoms of COVID-19.		
Average Incubation Period (time from infection to symptom onset) = 4 (with 2 days latency period)		
Estimates	5	(Ferretti et al., 2020)
	5,2	(Li et al., 2020)
	5,5	(Lauer et al., 2020)
	6,4	(Backer, Klinkenberg, & Wallinga, 2020)
	4 to 6 (Systematic review of 41 studies)	(M. Park, Cook, Lim, Sun, & Dickens, 2020)
Model Assumptions	5 (3 days latency & 2 days Asymptomatic)	(Norwegian Institute of Public Health - FHI, 2020a)
	6 (1 day of latency & 5 Asymptomatic)	(NTNU COVID-19 Taskforce, 2020)
	6 (2 days latency & 4 Asymptomatic)	(ISEE Systems, 2020)
	5,4	(Homer, 2020)
Hospitalised Infected		

Average Time to Hospitalisation after symptom onset = 5 days		
Estimates	9,1 to 12,5	(Li et al., 2020)
	1,5 to 5,5	(Sanche et al., 2020)
	5,76	(Gaythorpe et al., 2020)
	5,2 to 5,9	(Tindale et al., 2020)
Model Assumptions	5	(Ferguson et al., 2020); (Struben, 2020)
	9	(Norwegian Institute of Public Health - FHI, 2020a)
	6	(NTNU COVID-19 Taskforce, 2020)
Average Stay in Hospital before ICU admission = 3 days		
Model Assumptions	3	(Tuite et al., 2020 based on estimates by Wang et al., 2020)
	4	(NTNU COVID-19 Taskforce, 2020); (Norwegian Institute of Public Health - FHI, 2020a)
Average Stay in Hospital no Critical Care admission = 8 days		
Estimates	13,3	(Gaythorpe et al., 2020)*
	14,5	(Tindale et al., 2020)*
	11,5	(Sanche et al., 2020)
Model Assumptions	8	(Norwegian Institute of Public Health - FHI, 2020a); (NTNU COVID-19 Taskforce, 2020)
	10	(Tuite et al., 2020 based on estimates by Wang et al., 2020)
*no distinction between need for ICU admission and not		
Average Stay in Hospital before death = 8 days		
Estimates	8,6	(Linton et al., 2020)
	11.2	(Sanche et al., 2020)
Model Assumptions	8	(Ferguson et al., 2020); (Norwegian Institute of Public Health - FHI, 2020a)
	10	(NTNU COVID-19 Taskforce, 2020)
Critical Care Infected		
Average Stay in Critical Care before Recovery = Average Stay in Critical Care before Death = 12		
Estimates	16 to death; 20,51 to recovery*	(Gaythorpe et al., 2020)
	17,8 to death; 24,7 to recovery*	(Verity et al., 2020)
	14,5 to 20,2*	(Linton et al., 2020)
Model Assumptions	21	(Tuite et al., 2020 based on estimates by Yang et al., 2020)
	10	(Ferguson et al., 2020)
	12	(Norwegian Institute of Public Health - FHI, 2020a); (NTNU COVID-19 Taskforce, 2020)

*from *Symptom Onset*. Note that, Symptom Onset to death for those in Critical Care = 20, while Symptom Onset to death for Hospitalised = 15

Infectivity Module

The structure describing the infection rate is a modified version of the one developed by ISEE Systems in their COVID-19 model (2020) to account for two (2) significant mechanisms:

a) Modification of behaviour as a direct result of infection and/or testing
b) Declining Infectivity profile over the duration of the infection

As described earlier, in our brief description of SEIR models, the infection rate is equal to:

(Contact rate k * Susceptible S) * Infectivity b * (Infected I / Total Population N)

(Sterman, 2000, p. 302)

In a graphical representation, the aggregated infection rate and its causes are presented in Figure 8.

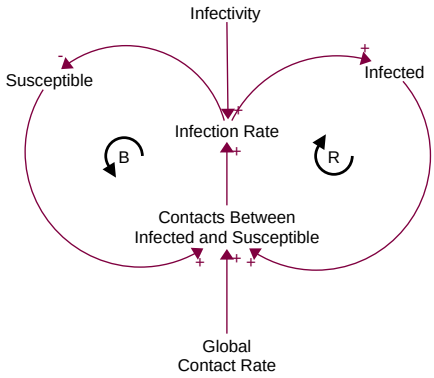


Figure 8: Determinants of Infection Rate, Aggregated View

The Infection rate is guided by two main loops, a Reinforcing loop of contagion and a Balancing loop of depletion (Sterman, 2000, p. 302). Infected individuals come in contact with Susceptible individuals at a (global) contact rate k. Contacts between a Susceptible and an Infected person have a probability equal to the infectivity to result in an infection. At the early stages of the spread of the virus, there are many Susceptible individuals who, after coming in contact with Infected individuals, might become themselves Infected, and pass on the infection to another Susceptible person the next time around. The reinforcing loop that is operating strongly at the early stages results in the exponential growth pattern of the COVID-19 spread that we have observed. As more and more people become Infected (and then Recover), the "pool" of Susceptible individuals in the population decreases and the Balancing loops gains more and more strength, leading to saturation in the total number of Infected. The two loops give rise to S-Shaped behaviour in the Recovered population.

To account for differences of the infection potential of different severity categories (see the following sections), we disaggregate this structure and develop an infection rate for each of the severity categories (see Figure 9)

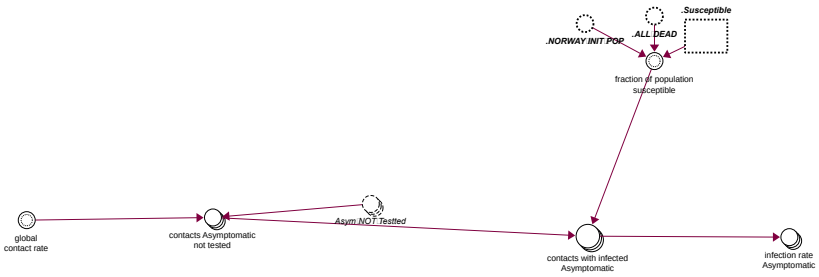


Figure 9: Infection Rate from Asymptomatic Infected

The number of Susceptible (S) and Total Population (N), as well as the Infected (I) at different stages and days of infection are direct inputs from the main viral model. The Global Contact Rate k is a function of the Baseline Contact Rate (the average "normal" number of contacts per person daily) and the reduction in contacts due to the behavioural response of the population. This behavioural reduction includes

i. a fractional *mobility reduction* due to social isolation
ii. an additional reduction of "dangerous" contacts due to the *total effect of hygienic behaviour on risk reduction*

Behavioural Dynamics Directly from infection

Infected individuals (I) are assumed to directly change their behaviour and reduce their contacts with others (Del Valle, Hethcote, Hyman, & Castillo-Chavez, 2005). This change can come directly due to the symptoms of the disease (people feeling unwell would more often stay at home), governmental instructions (quarantine), or individual decisions based on the status of knowingly posing a threat of infection to others. Our main assumptions are presented in Table 4. It is important to note that, due to no consideration of quarantine of close contacts (e.g. people at the same household or with multiple interactions with the infected person that would be expected to be quarantined under suspicion or confirmation of infection of the infected person), these assumptions might seem more strict than they might be in reality.

Table 4: Contacts adjustment as a direct effect of Infection status

Infection Status	**Value**	**Comments**
Asymptomatic	Equal to global contact rate	Asymptomatic individuals do not change their behaviour based on their status as infected as this status is not known to them.
Symptomatic	1 contact per day (10% of normal contacts)	Symptomatic Infected are assumed to reduce their contacts from the time they start experiencing symptoms & to generally comply with governmental instructions to "stay home" under suspicion of infection

Hospitalised (Hospitalized / Critical Care)	1 contact per week (1,45% of normal contacts)	Individuals who are hospitalized (or in Critical Care) do not have many chances of coming in unprotected contact with individuals around them.
Tested Positive	1 contact per week	Individuals who are tested positive for COVID-19 are assumed to comply with self-isolation protocols.

With this addition, the Infection rate from, for example a Symptomatic Infected person, looks like Figure 10. The main differences from Figure 8 above is in the Contact Adjustment for Symptomatic, and the utilisation of information regarding the day of Infection of the individual.

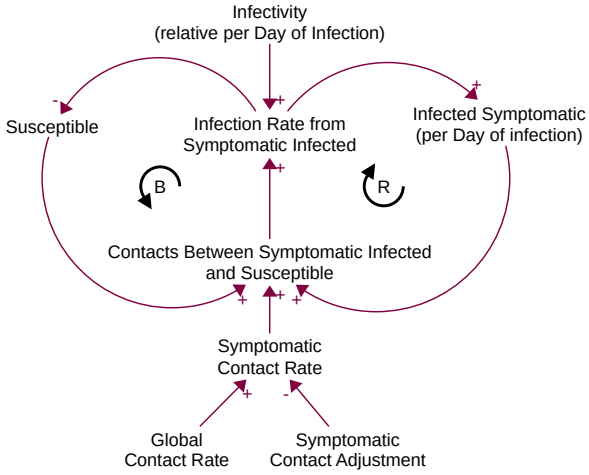


Figure 10: Infection rate from Symptomatic Infected

Infectivity: Declining Infectivity Profile & relative infectiousness of Asymptomatic

Evidence suggests that viral shedding, considered a main metric of infectiousness, declines over the duration of the disease (He et al., 2020; To et al., 2020; Wölfel et al., 2020; Zou et al., 2020). The information on the day of infection that each individual is at is utilised in this section of the model in order to assign the relative infectiousness according to the profile described by He et al. (2020) and presented in Figure 11. Similar assumptions of declining infectivity have been used in other models (Zhu & Chen, 2020).

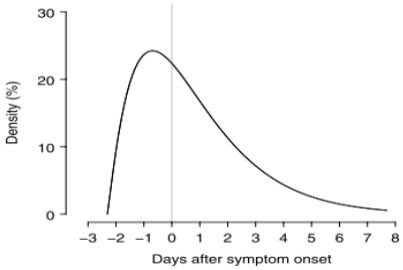


Figure 11: Infectiousness profile relative to days elapsed since symptom onset. Figure by He et al. (2020)

While there might be differences in the infection potential between infected of different severity categories, (e.g. Y. Liu et al., 2020), we do not have sufficient evidence to introduce such a differentiation except for the Asymptomatic Infected. The relative infectiousness of this population is still a quite uncertain factor but there have been evidence that it might be lower relative to those developing symptoms (Byambasuren et al., 2020). Despite the viral load potential, the mere presence of symptoms can, in this case, increase the probability that a contact can result in infection: "Since coughing and sneezing increase the amount of droplets that are expelled, the highest transmission potential (in absence of containment measures) seems to be for symptomatic individuals" (Sciensano, 2020, p. 7). The model used by the Norwegian health authorities uses an estimate of 10% relative infectiousness of Asymptomatic (Norwegian Institute of Public Health - FHI, 2020a), but, here, we decided to use the more modest estimate of 50% (Ferguson et al., 2020; Kucharski et al., 2020)

Testing Module

We represent the testing policies following the structure developed by ISEE systems in their COVID-19 model (2020). This structure can be considered as a somewhat simplified representation as it does not explicitly account for both positive and negative tests. Rather, it establishes *Target Test Rates* for the different severity categories than can only be achieved if sufficient testing capacity is in place. These Target Test Rates represent the maximum fraction of infected individuals at each severity category that can be identified through testing, given sufficient *Testing Capacity*. As such, they incorporate not only the ability to test an individual at any of the severity stages as deriving from the testing capacity and prioritisation decisions, but also the ability to *identify* an individual to be tested. The actual testing capacity of Norway is not known to us. Moreover, due to limited and prioritised testing, especially at the earlier stages of the virus spread, establishing the relationship between number of administered tests, fraction of positive tests, and overall prevalence of the virus in the population is a difficult feat that goes beyond the purpose of this model.

While the COVID-19 model from ISEE Systems represents the Target Test Rates as constant, behavioural validation from observed data, and knowledge of governmental practices led us to here conceptualise them as increasing relative to the Testing Capacity so as, the higher the Testing Capacity, the higher the Target Fraction for each severity category is (the assumptions used can be examined in Figure 12). The Norwegian Public Heath Institute - FHI (2020e) established rules for prioritised testing of suspected cases. As is to be expected, patients in need of hospital admission or in nursing homes with significant symptoms were the most prioritised. Our structure follows this prioritisation with higher target test rates in the most severe categories.

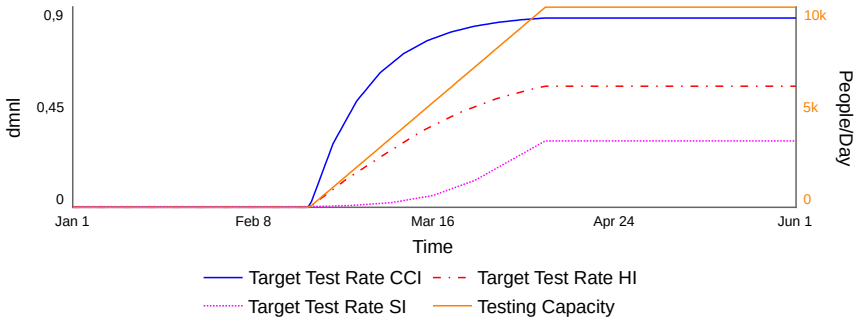


Figure 12: Target Test Rates for Symptomatic, Hospitalised, and Critical Care Infected (left-axis) and Overall Testing Capacity (right-axis)

Moreover, persons that have been in close contact with a confirmed case are also in one of the priority testing categories. The *Contact Tracing mechanism* takes as its input the number of recent positive tests and assumed both a number of *contacts tested per each positive test* and an *effectiveness of identification* (what fraction of these tests might be actually infected persons). This effectiveness is assumed to be 10% (1 positive identification per 10 contacts traced), and a 7-day delay between the first test and a test of a contact is assumed (*testing smooth time*) The contacts that are being traced per positive test are unknown – we assume a number that is increasing over time and various shapes and upper bounds can be experimented with (for the baseline assumption, see Figure 14 below).

Partial Testing of Main Infection Model

In this section, we will present the partial testing of main infection model to evaluate its ability to reproduce the data of the reference period (January 1st to June 1st). For a partial model testing, we use exogenous values instead of endogenously produced and the main assumptions and data used for this test are presented hereafter.

Mobility

The overall mobility of the population for the reference period was based on data by Institute for Health Metrics and Evaluation (IHME, 2020). We, moreover, assumed an adoption of hygienic behaviour by the population that leads to the magnitude of risk reduction presented in Figure 13.

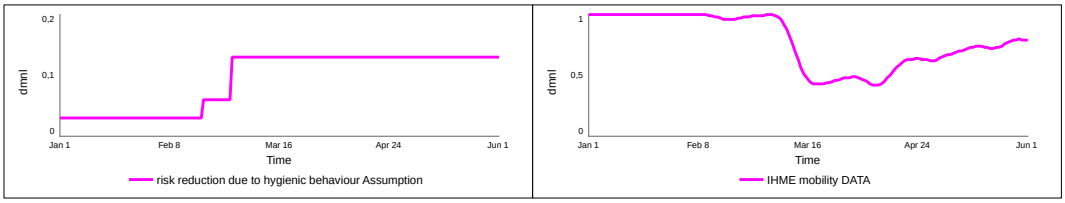


Figure 13: Assumptions used in Partial Model Testing: behaviour of Risk Reduction due to hygienic behaviour (left) and mobility reduction based on data (right) for the reference period

Testing

The assumption used for the daily addition in Testing Capacity was 200 tests per day, leading to the behaviour that can be seen in Figure 14. The Contact Tracing Mechanism also operates and, in the same graph, we present our assumptions for the number of contacts that are tested per positive test.

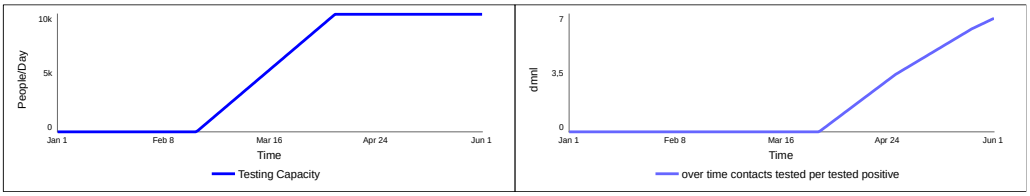


Figure 14: Assumptions used in Partial Model Testing: behaviour of the Testing Capacity (left) and of over time contacts traced per positive test (right) over the reference period

Main Feedback Mechanisms

As can be seen in the Causal Loop Diagram (CLD; Figure 15), as *Infected* come in contact with *Susceptible*, the Infection Rate increases, leading to more Infected the next time around (R loop). Higher Infection Rate means that fewer people remain Susceptible, reducing the probability of "*hot contacts*" (loop B1). This loop is not very strong during the reference period, as the Behavioural Response of the population (describing *Reduced Mobility* & *Hygienic Behaviour*) greatly reduces the *Global Contact Rate* (average daily contacts per person), and thus, the Infection Rate. Moreover, loops B2 and B3 that describe the contact reduction of quarantined Infected, either due to having been *Tested* (B2) or due to *Hospitalisation* (B3) further reduce contacts between Infected and Susceptible, both acting to hinder the spread of the virus. The strength of the B2 loop depends on the *Testing Capacity*: more Capacity makes the loop stronger and leads to lower number of Infected. The strength of B3 depends on characteristics of the virus, namely the fraction of Infected that become Hospitalised.

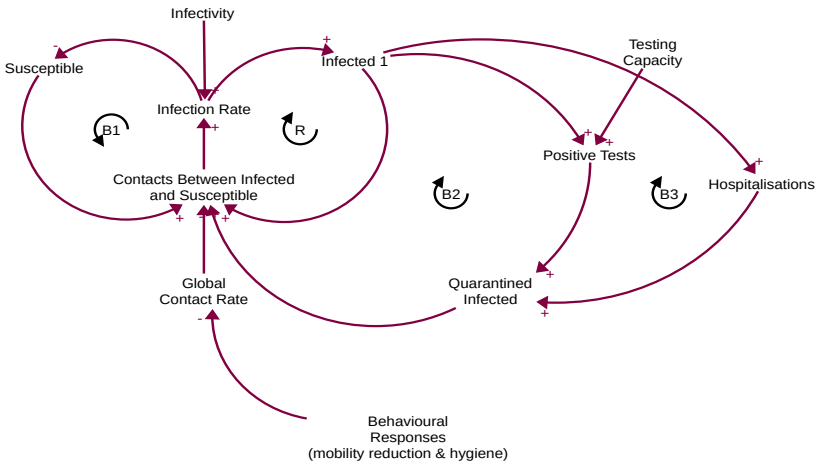


Figure 15: CLD of main loops leading to the spread of COVID-19

Results

In figure 16, we present the Daily New Infected, the Cumulative Tested Infected, as well as Cumulative Deaths, and compare them to data from the Norwegian Health Authorities. It is important to note that the data can only capture *confirmed* cases (Infected Tested).

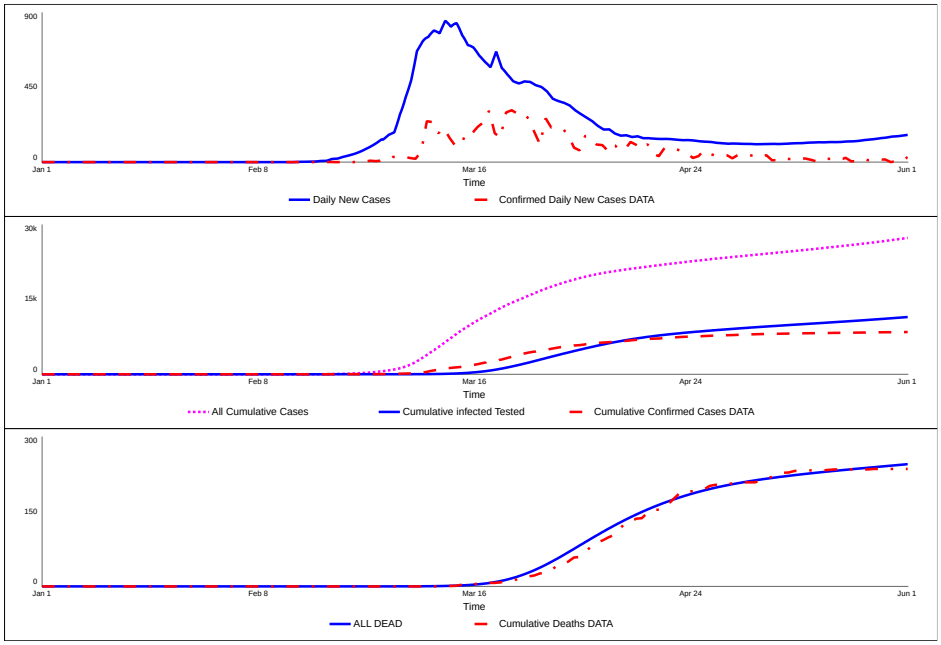


Figure 16: Results of Partial Model Testing: Daily New Cases, Cumulative Infected Tested, and Cumulative Deaths compared to data for the reference period

Our model seems to behave rationally during the reference period. Looking at the severity categories for which we have more information, namely Hospitalised Infected and Critical Care Infected, the behaviour fits the data quite (Figure 17)

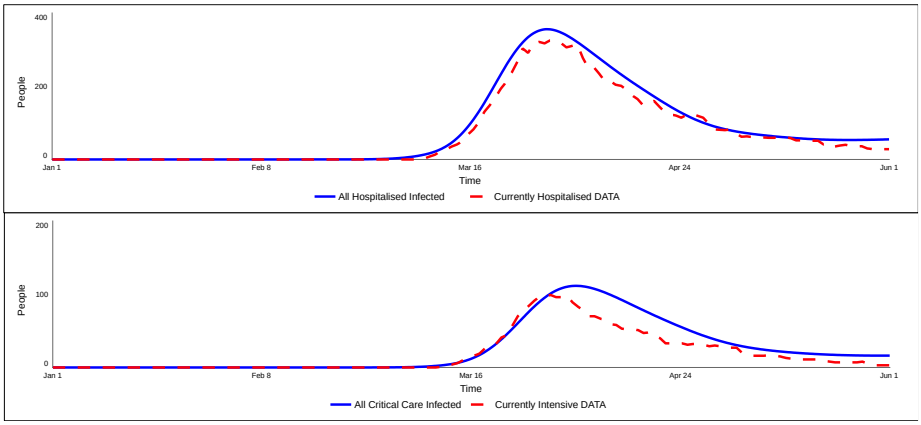


Figure 17: Results of Partial Model Testing: Hospitalised Infected (Current) and Critical Care Infected (Current) compared to data for the reference period

The overall behaviour in this case seems to fit quite well the behaviour of the real system, despite a small overestimation of the Critical Care Infected. Importantly, the growth in both Hospitalisations and Critical Care Admissions fits the observed growth in the data, providing evidence that the gradual progression structure that we have utilised, can accurately fit real-world observed values.

A final and significant comparison we need to perform is whether our model manages to approach estimates regarding the fraction of Infected falling under different Severity categories. The World Health Organization – WHO (2020) has suggested that, of all Infected, around 40% are Asymptomatic, 16-20% become Hospitalised, and 4-6% enter Critical Care. Other estimates point to 80% of Asymptomatic and Symptomatic, 15% requiring Hospitalisation and 5% as Critical. Those values come rather close to the ones produced by our model (see Figure 18), although we might be underestimating the fraction of Hospitalised and Critical Care Infected. It is important therefore to look for, perhaps more recent, information on this estimates as well as other parameters used in this model and update in order ensure that the model approaches better the appropriate fractions.

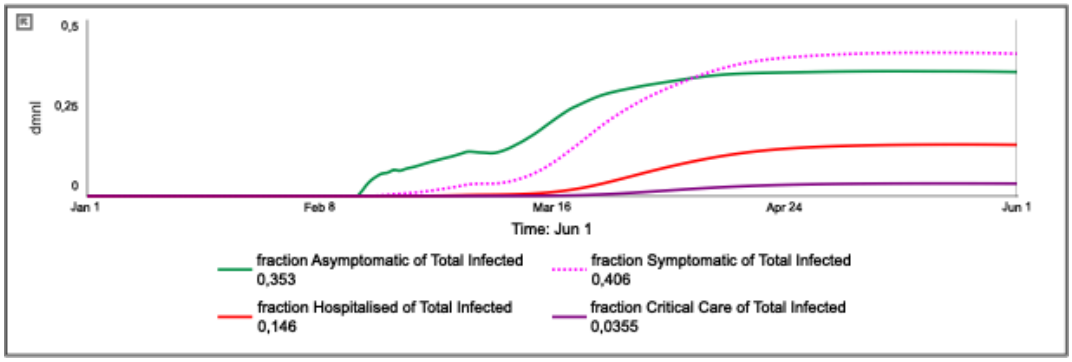


Figure 18: Results of Partial Model Testing: Fraction of (recovered) Infected at each of the severity categories

Moreover, our model captures the number of individuals at each severity category and according on day of their infection. In Fig.19 we see the total number of Symptomatic and Hospitalised Infected

(left), as well as Tested Symptomatic and Hospitalised (right) who are at a specific day of infection as indicated by the values of the x-axis (notice the different ranges of the y-axis for each graph). We can easily see the long-tail distribution that is expected as most individuals recover or move to the next category over time, as well as the "delay" in the movement of individuals to the next severity stage: the larger number of hospitalised patients are close to the 10th to 15th day of infection.

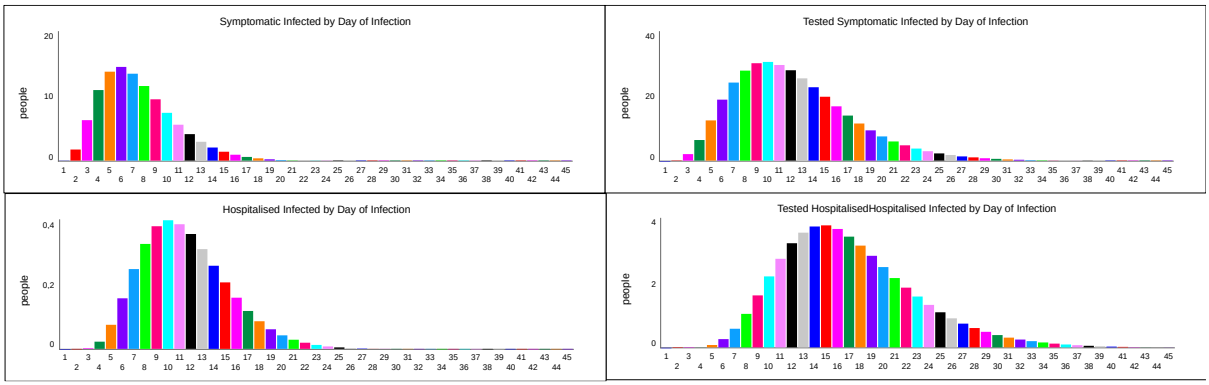


Figure 19: Partial Model Testing: Infected at each day of their infection

A test with no Contact Tracing

To look a bit closer into the behaviour of the model, we decide to run a Scenario with no Contact Tracing. We have evidence that contact tracing is a highly efficient mechanism for the management of COVID-19 (e.g. Matt J Keeling, Hollingsworth, & Read, 2020; Kucharski et al., 2020), and we would expect a higher number of New Infections and Deaths if it was not operating. As can be seen in Figure 20, the model does respond reasonably to the absence of the contact tracing mechanism (remember that we start slowly testing contacts at the end of April, hence differences before that date are not expected since the contact tracing is not in operation).

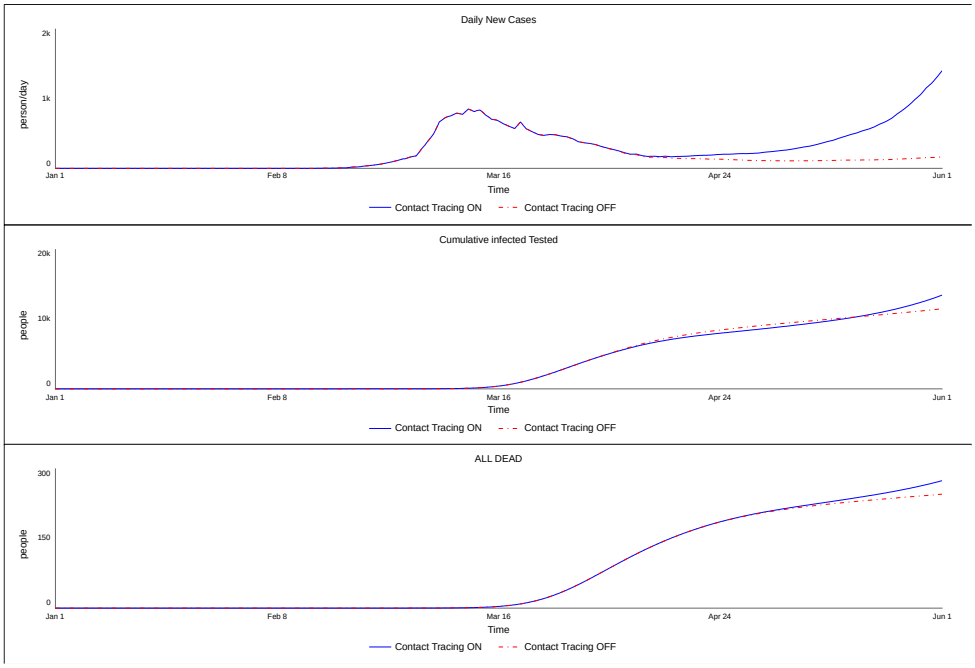


Figure 20: Results of Partial Model Testing of main Infection Model with and without the Contact Tracing mechanism

Overall our model seems to fit the curves of the data and behave rationally under reasonable assumptions (see the Validation section for a more detailed discussion).

Some comments on the Structure & Assumptions

Before moving to the Behavioural Model, we would like to address some issues

Are the relative fractions across severities correct?

We have tried to maintain the relative fractions of the different severity categories at reasonable levels, as can be seen in Fig 18. Those approach known estimates, but it is very important that they are revisited as new information are collected. We hope that serological tests, measuring the presence of antibodies, can provide better information on the actual prevalence of the virus in society through random sampling of the population. Different spread of infected at different categories can have implications for the estimation of the overall prevalence of the disease. Our model does not aim to provide policy suggestions aimed at handling the epidemic and as such, an even more accurate representation of its spread is somewhat outside our aim: here, we are particularly focused on the number of Severe cases (Hospitalised and Critical Care Infected), the number of Deaths, and the number of Tested Infected, as we will see in more detail in the next section. While optimally calibrating our model and continuously updating assumptions with latest information is necessary, we decide to leave this for the next iteration.

Is the testing mechanism sufficient?

For the purpose of our model, yes. For policy recommendations, no. The relationship between the number of performed tests, the overall prevalence of the virus in the population, and the probability per test to identify a positive case is a complex one and outside the boundaries of our model.

Is it reasonable that all people have the same probability of being infected or become hospitalised?

No. We have not dissagregated the population in age groups or geographically. Network dynamics in the population are significant for the spread of the disease (see, for example Isham, Kaczmarska, & Nekovee, 2011; M. J. Keeling & Eames, 2005)

Can the reduction in mobility as a direct effect of a COVID-19 infection be overestimated here?

Perhaps. We acknowledge that infected people would still have some contacts, especially if they were experiencing minor symptoms. However, we also know that close contacts of confirmed infected have been quarantined, a mechanism which we have not incorporated here. To somewhat mitigate for this, we have decided to use assumptions that are perhaps lower than the expected ones.

Chapter 3: Behavioural Dynamics

> "The overwhelming focus of governments' responses to the epidemic on behavioural responses of the population makes it incumbent upon researchers to be clear about how and why individuals act as the epidemic unfolds. What are their constraints and incentives? Will they voluntarily comply with directions given by public health o¢cials or do governments need to compel certain behaviours, as has now been seen across the world?"
>
> (Toxvaerd, 2020, p. 2)

As it hopefully became evident through the description of the main infection model, the spread of an infectious disease does not only depend on the characteristics of the viral agent. Infections occur *between people* and the scientific community is responding to what Squazzoni et al. termed "the COVID-19 modelling human behaviour challenge" (2020). The behaviour each individual decides to adopt is a very significant factor in the spread of a transmissible pathogen and "[e]ven gradual and mild behavioural changes can have a dramatic impact in slowing an epidemic" (Del Valle et al., 2005, p. 228). Moreover, not accounting for the behaviour of individual agents can impede our understanding of the viral agent, as it might lead to underestimations of its transmissibility or, at early-stage observations, predictions of a faster peak of the epidemic (Poletti, Ajelli, & Merler, 2011b, p. 5).

Due to their significance, epidemiological models that include behavioural dynamics are not rare (for a meta-analysis, see Funk, Salathé, and Jansen, 2010). In terms of methodology, *Game Theory* (von Neumann & Morgenstern, 1944; Weibull, 1995) has been a popular choice in decision making in epidemiological context (Chang, Piraveenan, Pattison, & Prokopenko, 2020; Poletti, Ajelli, & Merler, 2011a; Poletti et al., 2009; Reluga, 2010; Zhao, Bauch, & He, 2018) and economic epidemiological models have been applied specifically in the case of COVID-19 (Quaas et al., 2020; Toxvaerd, 2020 etc). Behavioural dynamics have also been included in models of COVID-19 in the field of SD (e.g. Homer, 2020; Struben, 2020).

Besides computational approaches, responses to threats posed by a health-related stimulus such as COVID-19 can draw upon long traditions in psychological research. *Health behaviour theories* are "a family of theories that were developed in health psychology or were adopted from research on attitude-behavior relations and goal pursuit to predict and understand health actions" (Sheeran et al., 2016, p. 3). Numerous theories of health-related decision making have been proposed and empirically evaluated (for a review, see M. Conner & Norman, 2005; Redding et al., 2000). Such theories, while not necessarily focusing on "crisis" situations as a global pandemic, provide meaningful insights to peoples' decisions to adopt or not a healthy behaviour such as, in our case, social isolation and other prophylactic measures.

To develop our dynamic hypothesis, we will look at main causal elements that computational approaches and health behaviour theories share.

Hypothesis & Theoretical Grounding

In this section, we will be presenting our main assumptions for the variables we will be using in our model and their connections. To do so, besides the overall literature review, we will present a process of "theoretical grounding", part of the "multi-grounded theory" proposed by Goldkuhl & Cronholm (2003). Theoretical grounding is a process where "the evolving theory is confronted with other existing theories" (p.5) and was used here to evaluate our hypothesis as it compares to known theoretical constructs and theories. Hence, for each of the main assumptions and links, we will present a brief review of the literature, our main hypothesised variables and causal connections, and we will look at whether those variables and connections are present at and supported by the main Health Behaviour Models we have utilised to propose our combined theory. The theories we will consider for the theoretical grounding process are:

i. the **Health-Belief Model (HBM**) (Champion & Skinner, 2008; Rosenstock, 1974; Sheeran & Abraham, 1996)
ii. **Protection Motivation Theory (PMT)** (Floyd, Prentice-Dunn, & Rogers, 2000; Maddux & Rogers, 1983; Rogers, 1975; Rogers & Mewborn, 1976)
iii. the **Theory of Reasoned Actions (TRA)** (Fishbein & Ajzen, 1975) & the later developed **Theory of Planned Behaviour (TPB)** (Ajzen, 1985; Madden et al., 1992)
iv. the **Transtheoretical Model** (DiClemente & Prochaska, 1982; Prochaska & DiClemente, 1983)
v. **Cognitive appraisal theory (CAP)** (Folkman, Lazarus, Dunkel-Schetter, DeLongis, & Gruen, 1986; Lazarus & Folkman, 1984)
vi. the **Extended Parallel Process Model (EPPM)** (Witte, 1992, 1994, 1995; Witte & Allen, 2000)
vii. the **Health Action Process Approach (HAPA)** (Ralf Schwarzer, 1992, 2001; Ralf Schwarzer & Fuchs, 1995)

Due to the multiple mechanisms, we will begin by presenting the main Drivers and main loops of the behaviour. Then, we will briefly reiterate those main mechanisms and their effect on the spread of COVID-19 before continuing to additional ones.

Drivers of Behaviour

Intention

As we have described earlier, the behaviour that is relevant for and will feed back to the main Infection model is the actual adoption of a prophylactic behaviour (here, *mobility reduction* and *level of adoption of other hygiene measures*). Behaviour has, in many Health Behaviour models, conceptualised as being distinct from the *intention* to adopt the behaviour (see table 5). Intention is considered to precede and lead to the enactment of the target behaviour (when behaviour is explicitly considered). Game Theoretical approaches tend to view behaviour as emanating from an evaluation of costs and benefits associated with it. We perceive intention to be a good proxy for an evaluation of the benefits associated with the behaviour: to build an intention, one is expected to perceive that there are some benefits of the behaviour.

We will follow the term used by Protection Motivation Theory (PMT) & by the Extended Parallel Process Model (EPPM) and term this intention to adopt the proposed behaviour *Protection Motivation*. Protection Motivation has a positive relationship with *Prophylactic Behaviour*: higher Motivation leads to higher adoption of the Behaviour (Table 5)

Model Variables & Connections				
Variable	**Description**	**Influencing**	**Polarity**	
Protection Motivation	The motivation to act to mitigate an environmental Threat	Prophylactic Behaviour	+	Protection Motivation → (+) Prophylactic Behaviour

Theoretical grounding							
Concept	**Theory**						
	HBM	**PMT**	**TRA/TPB**	**EPPM**	**CAT**	**TM**	**HAPA**
Intention Distinct from & leading to behaviour?	**N/E**	Behaviour not considered	**Y**	Behaviour not considered	**N/E**	**Y**	**Y**

Table 5: Relationship between Intention and Behaviour

Y=Yes, N=No, N/E=Not Explicit. HBM: Health Belief Model, PMT: Protection Motivation Theory, TRA/TBA: Theory or Reasoned Action/Theory of Planned Behaviour, EPPM: Extended Parallel Process Model, CAT: Cognitive Appraisal Theory, TM: Transtheoretical Model; HAPA: Health Action Process Approach

Perceived Costs of the Prophylactic Behaviour

As mentioned above, Game Theoretical approaches propose that individuals, when deciding on what strategy to follow (here, to adopt the protective behaviour or not), weight the payoffs, the values associated with each strategy (Chang et al., 2020). Costs of a given strategy or behaviour are however

usually used experimentally in such approaches: by manipulating the costs relative to benefits, researchers can examine equilibrium solutions for such systems (REFS). Health Behaviour models also incorporate Costs and, while the weighting process does not assume the same degree of rationality common to Economical and Game Theoretical models, Costs considerations represent various hindrances or resistance towards adopting the new behaviour.

In terms of evidence on the relationship between Costs and Behaviour, meta-analyses conducted by Milne, Sheeran, & Orbell (2000) and by Floyd, Prentice-Dunn, & Rogers (2000) under the framework of Protection Motivation Theory found that costs associated with the proposed response had significant effects in eliciting favourable responses (for a discussion, see Norman et al., 2005). Prochaska et al. (1994), performing research under the Transtheoretical Model, found that the cons of changing a behaviour outweighed the pros only at the Action and Maintenance stages of behaviour adoption rather than in the Pre-Contemplation and Contemplation stages, providing evidence that the main contribution of costs is on the actual Behaviour rather than the intention (Protection Motivation).

Different behaviours have different associated costs, so we use here the term *Perceived Costs of Prophylactic Behaviour* denoting that we are referring to the costs of a specific prophylactic behaviour. Costs influence behaviour directly and in a negative direction: the higher the Perceived Costs of a behaviour the lower the adoption of the Behaviour (Table 6).

Model Variables & Connections				
Variable	**Description**	**Influencing**	**Polarity**	
Costs of Prophylactic Behaviour	The Costs associated with performing a specific prophylactic behaviour	Prophylactic Behaviour	-	Prophylactic Behaviour ← Perceived Costs of Prophylactic Behaviour

Theoretical Grounding							
Concept	**Theory**						
	HBM	**PMT**	**TRA/TPB**	**EPPM**	**CAT**	**TM**	**HAPA**
Costs of Proph. Behaviour present?	Y	Y	Y	N	Y	Y	Y
Costs directly Influencing behaviour?	N	Behaviour not considered	Y	-	Y	Y	Y

Table 6: Relationship between Costs of Prophylacitc Behaviour, Protection Motivation, and Behaviour
Y=Yes, N=No, N/E=Not Explicit. HBM: Health Belief Model, PMT: Protection Motivation Theory, TRA/TBA: Theory or Reasoned Action/Theory of Planned Behaviour, EPPM: Extended Parallel Process Model, CAT: Cognitive Appraisal Theory, TM: Transtheoretical Model; HAPA: Health Action Process Approach

Drivers of Protection Motivation

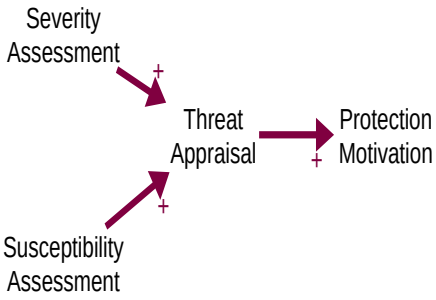
Threat Appraisal

Most computational models take as main cause of the response of the population information regarding the prevalence of the disease (termed usually "prevalence-elastic response", Funk, Salathé, et al., 2010, p. 1247). Explicit or implied to the connection between the disease's prevalence and the behavioural response is the perception of what is usually referred to as the "risk" of contracting the disease

This notion of risk is usually utilised in Game Theoretical and other approaches as an input to the previously described cost/benefit process that is believed to guide adoption of a specific response. Thinking of risk as a cost, it is not unusual that it incorporates not only the probability of infection but an evaluation of the consequences of infection. **Susceptibility Assessment** (the perceived probability of getting infected) and **Severity Assessment** (how severe would the consequences of infection be for me) are present in most of the main health behaviour models as well (see table XXX) as drivers of one's perceptions of risk or Threat, as we use in this context.

The inclusion of both assessments also makes sense for the specific case study. Let us consider the early stages of the pandemic and the notion of COVID-19 being "like a normal flu" (see for example Grady, 2020). This comparison was, for good reason, considered as dangerous by public health authorities who issued statements to counteract it (WHO, 2020). While it can be argued that many people indeed considered that they have a high probability of getting the disease, the fact that it was considered "no more dangerous than the flu", could reduce the likelihood of avoiding getting infected by it. In our model, we will incorporate Susceptibility and Severity Assessments as the individual's compound *Threat Appraisal*: the perception of the Threat that is posed to the individual's wellbeing by COVID-19. Both Assessments have a positive relationship to Threat Appraisal: higher Assessment of Susceptibility or Severity lead to higher overall Threat Appraisal. This Threat Appraisal, in turn, has a positive relationship with Protection Motivation: the higher the individual perceived the Threat to be, the more Motivated they are to be protected against it (Table 7).

Model Variables & Connections				
Variable	**Description**	**Influencing**	**Polarity**	
Threat Appraisal	The perception of the Threat posed by COVID-19	Protection Motivation (intention)	+	

Susceptibility Assessment	The assessment of the likelihood of contracting the disease	*Threat Appraisal*	+	
Severity Assessment	The assessment of the severity of consequences from the disease	*Threat Appraisal*	+	

Theoretical Grounding							
Concept	**Concept Identified per Theory**						
	HBM	**PMT**	**TRA/TPB**	**EPPM**	**CAT**	**TM**	**HAPA**
Threat Appraisal distinct?	**Y**	**Y**	**Y[1]**	**Y**	**Y**	**N/E**	**Y**
Including Perceived Susceptibility?	**Y**	**Y**	**Y[1]**	**Y**	**Y**	**N/E**	**Y**
Including Perceived Severity?	**Y**	**Y**	**Y[1]**	**Y**	**Y**	**N/E**	**Y**
Influencing intention?	Y (Janz & Becker, 1984)	Y	Y[1]	Y & Initiates Efficacy Appraisal	Initiates Efficacy Appraisal	-	Y & Initiates Efficacy Appraisal

1. "Attitudes" is the term used to represent people's "beliefs about the likelihood of various consequences of particular actions, combined with the person's evaluations of those consequences" (Smith & Stasson, 2000, p. 447). We perceive this notion to be conceptually very close to our definitions of Threat Appraisal and the inclusion of Susceptibility Assessment (likelihood of infection) and Severity Assessment (evaluation of consequences).

Table 7: Relationship between Severity, Susceptibility, Threat Appraisal, and Protection Motivation

Y=Yes, N/E=Not Explicit. HBM: Health Belief Model, PMT: Protection Motivation Theory, TRA/TBA: Theory or Reasoned Action/Theory of Planned Behaviour, EPPM: Extended Parallel Process Model, CAT: Cognitive Appraisal Theory, TM: Transtheoretical Model; HAPA: Health Action Process Approach

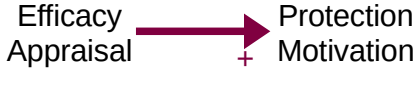
Efficacy Appraisal

The notion of Efficacy as a subjective perception has also been prominent in various frameworks. In Game Theoretical approaches, especially pertaining to collaborative games, Efficacy has been described as "an individual's estimate of the impact of their contribution on the likelihood of public good production" (Kerr, 1992 in Dijkstra & Bakker, 2017). In Health Behaviour models, it has been defined the belief of the individual in their ***capacity to prevent*** potential harmful outcomes from a potentially harmful encounter (Folkman et al., 1986; in L. Wang & Lin, 2020). More specifically, in the Extended Parallel Process Model, efficacy is conceptualised as pertaining to the perception of ''...the

effectiveness, feasibility, and ease with which a recommended response impedes or averts a threat.'' (Witte, Cameron, McKeon, & Berkowitz, 1996, p. 320). Efficacy has also been described as involving two concepts: self-efficacy (belief about our own ability to respond adequately) and response efficacy (whether the proposed response works to mitigate the threat) (Witte & Allen, 2000).

While results on the effect of Efficacy vary, especially when both self-efficacy and response-efficacy are studied, perceptions of efficacy have been consistently found to increase individual contributions to common-good causes (Kerr, 1992, 1996) and adoption of health protective behaviours (e.g. Floyd et al., 2000; O.-H. Park, Hoover, Dodd, Huffman, & Feng, 1989; Webster et al., 2020)[3]. The latter was also observed for the case of COVID-19 (L. Wang & Lin, 2020) and hypothetical scenarios of epidemics (Timpka et al., 2014). Research suggests that Threat (or fear) appeals are more effective when coupled with Efficacy messages (see, for example Ruiter, Kessels, Peters, & Kok, 2014; Tannenbaum et al., 2015). It follows then that including Efficacy is a reasonable choice as there are evidence that people perceiving a Threat is not sufficient to elicit the optimal response: they need to know that they can perform some action(s) that can reduce the threat.

In our work, we do not separate self-efficacy from response efficacy as we believe that elements of self-efficacy for the case of an infectious disease are distributed between response efficacy beliefs and Costs of the Prophylactic Behaviour (I can successfully perform the behaviour if the Costs are manageable). We therefore use the term *Efficacy Appraisal* to describe the overall belief that the proposed responses can efficiently act to mitigate the environmental Threat. Efficacy has a positive relationship with Protection Motivation (intention) so as, higher Efficacy Appraisals leads to higher Protection Motivation.

Model Variables & Connections				
Variable	**Description**	**Influencing**	**Polarity**	
Efficacy Appraisal	The perception of how efficient a proposed response is in mitigating the Threat	Protection Motivation (intention)	+	

Theoretical Grounding							
Concept	**Theory**						
	HBM	**PMT**	**TRA/TPB**	**EPPM**	**CAT**	**TM**	**HAPA**
Efficacy Appraisal as a distinct process?	**Y**	**Y**	**Y** [Perceived Behavioural Control[1]]	**Y**	**Y**	**N/E**	**Y**
Influencing Protection	Y	Y	Y	Y	Y	N/E	Y

[3] And, even other types such as pro-environmental behaviour (Keshavarz & Karami, 2016).

Motivation (intention)			& less strongly behaviour				(also initiates Self-Efficacy Evaluation)
1. Perceived Behavioral Control describes "beliefs concerning whether one has access to the necessary resources and opportunities to perform the behaviour successfully, weighted by the perceived power of each factor" (Mark Conner & Sparks, 2005, p. 175)							

Table 8: Relationship between Efficacy Appraisal and Protection Motivation

Y=Yes, N=No, N/E=Not Explicit. HBM: Health Belief Model, PMT: Protection Motivation Theory, TRA/TBA: Theory or Reasoned Action/Theory of Planned Behaviour, EPPM: Extended Parallel Process Model, CAT: Cognitive Appraisal Theory, TM: Transtheoretical Model; HAPA: Health Action Process Approach

The interaction between Threat Appraisals and Efficacy Appraisals

While most models differentiate between appraisals of the actual Threat and appraisals of the Efficacy, Cognitive Appraisal Theory and the Extended Parallel Process Model make explicit mention of how this comparison can elicit adaptive or maladaptive behavioural responses. For Cognitive Appraisal, coping can be either problem-focused or emotion-focused, with the former describing coping efforts "intended to alter the source of stress by acting on it directly" (Forsythe & Compas, 1987, p. 474) while the later focuses on moderating the emotional responses to the Threat. In a very similar way, the Extended Parallel Process Model differentiates between Danger Control and Fear Control responses. Danger Control, like problem-focused coping, leads individuals to accept the recommendations of the message, while Fear Control describes "Coping responses that diminish fear, such as defensive avoidance, denial, and reactance (including issue/message derogation and perceived manipulative intent)" (Witte et al., 1996, p. 320). In both theories, responses that lead individuals to act against the Threat by adopting the proposed behaviour (Problem-focused or Danger Control) can be achieved if the Threat Appraisal is sufficient and if the Efficacy Appraisal outweighs the Threat Appraisal, that is if the individuals believe that a) there is a significant Threat and b) there is something that *can* be done to mitigate that threat. This has been supported by a meta-analysis by Witte & Allen (2000), who found that the best results in terms of protective behaviours can be achieved through strong fear appeals combined with high-efficacy messages. Support for this has been provided in different context as well although the actual observed relationship varies between contexts and for different ranges of Threat and Efficacy values (Carcioppolo et al., 2013; Dias, Cruz, & Fonseca, 2012; Krieger & Sarge, 2013; Schneider & Kenny, 2000). There is however an agreement that increases in Threat Appraisals, when combined with low Efficacy (Response & Self-Efficacy) can actually weaken intention to adopt a behaviour (the "boomerang" effect, see Sturges & Rogers, 1996).

Mathematically, Witte initially proposed that the relationship between Threat and Efficacy is a multiplicative one (1994) and later went on to describe it as a subtraction of the Threat assessment from the Efficacy assessment (Witte, 1995; Witte et al., 1996). This relationship has been debated amongst

other researchers (for a brief review, see Cismaru & Lavack, 2007, pp. 259–261) and, here, instead of an additive or multiplicative relationship, we adopt a weighted average approach as proposed by N. Weinstein (1993). This weighted average is used to "combine" the effects of both Threat and Efficacy Appraisal in the Protection Motivation. We do however incorporate an additional mechanism (a "multiplier") that aims to capture the region of "Emotion-Focused Response" or "Fear Control" which are not otherwise explicitly examined. This multiplier ensures that, if Threat outweighs Efficacy to a significant degree, Protection Motivation will diminish.

The story so far: A top-level view of relationships

Let us briefly reiterate the main relationships described above before continuing.

Individuals, when confronted with a Threat like COVID-19 engage firstly in an assessment of that Threat (**Threat Appraisal**). Threat Appraisal is hypothesised to have two components: the **Susceptibility Assessment** (the perceived probability of becoming infected with the virus) and the **Severity Assessment** (how severe the consequences of infection would be). Threat Appraisal alone is not enough to motivate action; they need to assess whether there is an effective response (**Efficacy Appraisal**). Those two elements, Perceived Threat and Perceived Efficacy are compared with each other to comprise the individual's motivation to act against the Threat (**Protection Motivation**). If the individual is facing a severe Threat *and* has an Effective response against it, Protection Motivation will be high. If they do *not* believe that there is something they can do about the threat (low Perceived Efficacy) or that there is *not*, in fact, a significant threat (low Perceived Threat), their Protection Motivation will be low.

Protection Motivation describes an "intention", however whether an individual will actually engage in the behaviour depends on their evaluation of the **Costs of the Prophylactic Behaviour**. If the Costs are very high or their Protection Motivation very low, they will *not* adopt the behaviour, at least not with the same intensity that they would were they faced with lower costs of higher motivation.

In the case of an infectious disease like COVID-19, adoption of the behaviour has an effect on the actual environmental Threat: as people practice social isolation for example, fewer contacts between Infected and Not-Infected lead to fewer New Infections. Fewer Infections reduce the Perceived Threat in the environment, leading to reduced Protection Motivation and, thereby, lower adoption of the Prophylactic Behaviour the next time around. This relationship forms a Balancing Loop that acts to slow down the spread of COVID-19.

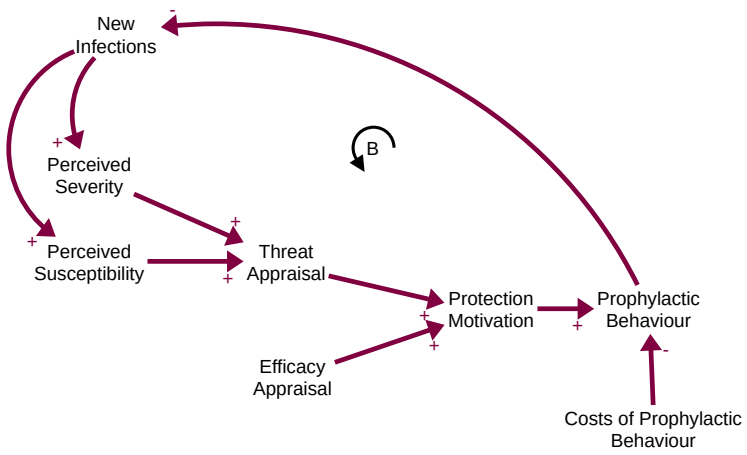


Figure 21: Top-Level View of Feedback between the Infection sub-Model and the Behavioural sub-Model

Due to the significance of this loop for the spread of the epidemic, numerous questions arise:

i. Are Threat Appraisals only grounded in the actual prevalence of the virus or is there some additional element that can be addressed by policies?
ii. Is Efficacy Appraisal a static or a dynamic concept?
iii. What can be considered the Costs of Prophylactic Behaviour?

Drivers of Threat & Efficacy Appraisals

Observations of the Environment

Actors are expected to look directly at their environment to make estimations regarding the Threat as well as the Efficacy of the proposed response that can mitigate that Threat. In the case of Threat Appraisal, we have already described it as the compound Susceptibility and Severity Assessments (assessments regarding the probability of a COVID-19 infection and the consequences of infection respectively). Those assessments are expected to a large degree to come from observations regarding the spread of the virus, as those are disseminated by the country's health authorities.

In the case of Susceptibility Assessment, computational approaches conceptualise often the perceived risk of infection as coming from the disease prevalence, the infected fraction of the population (e.g. Poletti et al., 2011b; Toxvaerd, 2020). In the case of COVID-19, Glöckner, Dorrough, Wingen, & Dohle (2020) observed across three studies at different phases of the COVID-19 infection in Germany an inverse U-shaped pattern in the reported probability of infection and probability of hospitalisation (see Figure 22).

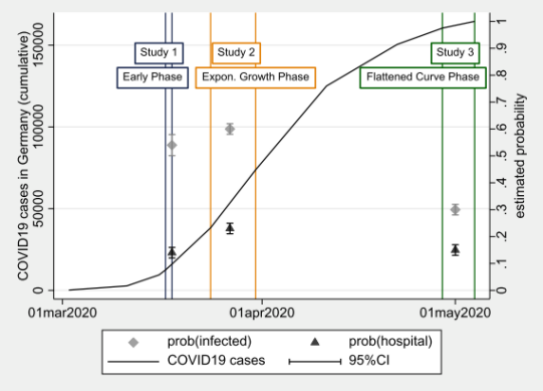


Figure 22: Risk Perception plotted against the development of COVID-19 cases in Germany. Figure by Glöckner et.al (2020, p. 40)

This "inverted U-shaped pattern" seems to correspond well to the relative change in infections, the New Daily Cases. In our model, we use the *Reported and Perceived New Cases per 10000 Susceptible* (that is, the daily new confirmed through testing cases) as the input to the *Observations Contribution to Susceptibility Assessment.*

In the case of the Severity Assessment, the observational mechanism is quite similar but taking here as its input the number of *Perceived Severe Cases*: The Daily new Hospitalisations and Critical Care Admissions, as well as the Daily New Deaths as those are reported by authorities and perceived by an average individual. Unlike in the case of the Susceptibility Assessment, we view the *Perceived Severe Cases* as an explicit stock as so to capture a "fading-memory mechanism" like the one described by Poletti et al. (2011b). We believe this is justified as the news of a more severe case or a death might persist longer in peoples' memory – they are not "forgotten" as fast as a new case is expected to.

Lastly, in the case of the Efficacy Appraisal, the picture is not as clear, especially since the actual efficacy of the response (the actual "success" of a proposed action) can only be assessed over much longer periods of time. Due to the need for an endogenous Efficacy Appraisal, we made here the assumption regarding environmental Efficacy cues as being grounded to the perception of the population's compliance with the proposed response. This mechanism is describing a process whereby individuals' perceptions of the population's engagement with prophylactic behaviours (*mobility reduction* and *level of adoption of other hygienic behaviour*) inform their appraisals about the Efficacy of those proposed responses. This is perhaps not unreasonable since the actual efficacy of the proposed measures in the case of COVID-19 or other infectious diseases depends precisely on the level of their adoption by the population, however, the proposed mechanism implies that individuals are also aware of this fact. We have decided to also include some level of "optimism" in this perception for our case study as we believe that the Norwegian population in general tends to follow governmental advice and this is known amongst individuals (simply put, people expect that others will comply to a larger extent that we would perhaps observe in other countries). As such, people "overestimate" the compliance of the population relative to their direct observations (Fig. 23)

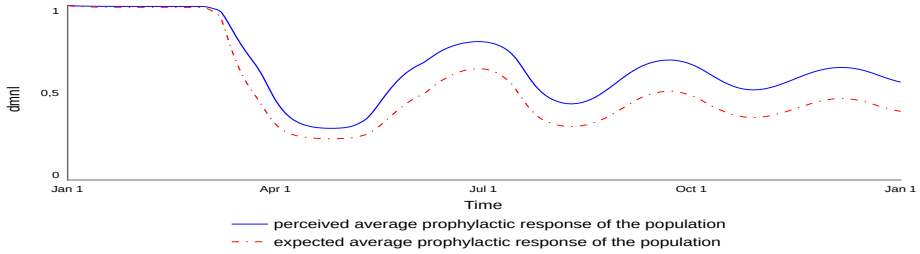
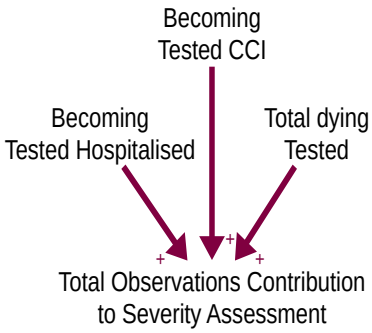
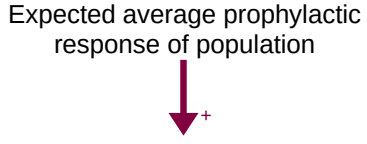


Figure 23: The over-time development of the perceived average prophylactic response of the population and that of the "optimistic" expectation (expected average prophylactic response)

The relationships are summarised in Table 9.

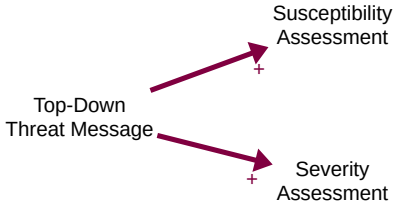
Table 9: Observations and their contribution the Threat- and Efficacy-Related Appraisals

Model Variables & Connections				
Variable	**Description**	**Influencing**	**Polarity**	
Reported and Perceived Daily New Cases	Daily new confirmed Covid-19 infections as reported by the government and perceived by an average individual	Total Observations Contribution to Susceptibility Assessment	+	
Becoming Tested Hospitalised	Daily new Covid-19 confirmed hospitalisations as reported by the government and perceived by an average individual	Total Observations Contribution to Severity Assessment	+	
Becoming Tested CCI	Daily new confirmed Covid-19 Critical Care admissions as reported by the government and perceived by an average individual	Total Observations Contribution to Severity Assessment	+	
Total dying tested	Daily new confirmed Covid-19 deaths as reported by the government and perceived by an average individual	Total Observations Contribution to Severity Assessment	+	
Expected average prophylactic response of population	The expected, due to observations adjusted with some optimism, average adoption of prophylactic responses by the population	Total Observations Contribution to Efficacy Appraisal	+	

Top-Down Information distribution

A second mechanism influencing Threat and Efficacy Appraisals is information distribution. We follow here a "double-avenue" proposed also by Kiss, Cassell, Recker, & Simon (2010) of both a Contact-based and a Population-wide transmission of information. Public awareness is indeed influenced heavily by population-wide information provided by Health Authorities and governments through Top-Down messages (for a brief review, see Dryhurst et al., 2020; Khosravi, 2020). Our assumption is that, at least in the case of COVID-19, Top-Down information are not only including data regarding the disease (as described in the previous section) but also efforts of authorities to explicitly address the population through communication messages aiming to raise awareness. Such messages are considered to emphasize both the Threat posed by the virus and how the proposed response can efficiently mitigate that Threat (*Top-Down Threat*-or *Efficacy-Related communication message*). Examples of such messages can be considered press conferences, explicit statements, etc. Some Health Behaviour models do include centrally distributed information and knowledge and, when they do, those tend to be considered as influencing Threat and Efficacy Assessments (see Table 10). Threat-Related messages emphasise the "seriousness" of COVID-19 both in terms of infection potential and consequences. Efficacy-Related messages can contain both scientific information about the efficiency of the proposed responses and "emotional" messages aiming to raise the population's perception that "we can fight the threat".

In our model, we represent the communication decision by the government as the *Top Down Threat-Related Communication Message* and the *Top Down Efficacy-Related Communication Message*. Those communication messages have direct positive effects on the Threat Appraisal (Susceptibility and Severity Assessments) and on the Efficacy Appraisal respectively, as well as an indirect effect through the Bottom-Up information diffusion mechanism that we will describe more detail in the next section.

Model Variables & Connections				
Variable	**Description**	**Influencing**	**Polarity**	
Top Down Threat-Related Communication Message	The communication message by government regarding the Threat posed by COVID-19	Susceptibility Assessment	+	
		Severity Assessment	+	
Top Down Efficacy-Related Communication Message	The communication message by government regarding the efficacy of	Efficacy Appraisal	+	

	proposed responses to mitigate COVID-19					
Theoretical Grounding						
Concept	**Theory**					
	HBM	**PMT**	**TRA/TPB**	**EPPM**	**CAT**	**TM**	**HAPA**
Information	**Y**	**Y**	**Y**	**Y**	**N**	**N**	**N**
Influencing Threat and Efficacy Appraisals?	Intention / behaviour (Champion & Skinner, 2008) or Threat Appr. (Janz & Becker, 1984)	Y	Y	Y			

Table 10: Relationship between Top-Down Information & Threat and Efficacy Appraisals

Y=Yes, N=No, N/E=Not Explicit. HBM: Health Belief Model, PMT: Protection Motivation Theory, TRA/TBA: Theory or Reasoned Action/Theory of Planned Behaviour, EPPM: Extended Parallel Process Model, CAT: Cognitive Appraisal Theory, TM: Transtheoretical Model; HAPA: Health Action Process Approach

While this decision rule of Top Down message communication is of course influenced by many mechanisms, we ground both messages in the government's response to *New Reported Infections*, the daily confirmed cases of COVID-19. Due to the global nature of the pandemic, we include an additional mechanism of "early" risk identification by the government which is more sensitive to the presence of new cases (the *Additional Top-Down Communication* mechanism which is effected by the *Perceived by government trend of growth of new cases*). In both cases, governments look at the confirmed new cases at hand and respond by sending out Threat and Efficacy-Related messages.

Bottom-Up Information & Network effects

The idea that ideas, information, trends, etc. spread in a way similar to a spread of an infectious disease is far from new (Bass, 1969; Goffman & Newill, 1964). Processes of social contagion (see Sterman, 2000, Chapter 9) account for the diffusion of information (e.g. Liao & You, 2014), awareness (Funk, Gilad, & Jansen, 2010; Funk et al., 2009), as well as that of emotional responses to epidemics among the population such as fear (Epstein et al., 2008). Fear, while a distinct concept describing an emotional response to threat, can be considered to be strongly related to the dependent on the cognition of Perceived Threat (Witte & Allen, 2000). We have therefore decided to use diffusion processes for the spread of information and cognitions (Appraisals) related to both the Threat and the Efficacy of the response. While, in our model, individuals also look at their environment to make estimates regarding a) the efficacy of the behaviour due to the levels of adoption they observe in the population, and b) the social costs of the behaviour, we do not utilise diffusion processes per se for those environmental impacts.

To describe information dissemination via a Bottom-Up mechanism, we develop a contagiousness structure where people who are Unaware of COVID-19 become Aware via information disseminated by Norwegian media and via their social networks. The Aware population can become Actively Aware, that is become actively concerned about COVID-19 and more likely to disseminate information. Our assumption is that this movement is controlled by the Susceptibility Assessment: the higher the perceived probability of infection, the more likely it becomes that the individual becomes alarmed and active. This state of being alarmed declines over time as the individual is expected to experience some fatigue from information. We believe this fatigue to be influenced by a person's Severity Assessment: if the consequences of the virus are expected to be very high, people remain Actively Aware longer (they are more "immune" to fatigue because of their perception of the situation's severity). Lastly, drawing from the literature on complex contagions (Centola, 2010; Sprague & House, 2017), we have decided to include a state of Recovered individuals in line with hypotheses that people who are "new" in their concerns regarding the virus (Actively Aware) are sharing more instensly, while people who have gone through that state before (Recovered) are less active. With a high enough level of perceived probability of infection (Susceptibility Assessment), those individuals can enter again the state of being Actively Aware and thus "high spreaders" of information. Those states are summarised in Table 11.

Table 11: States of Awareness of the Top-Down Information Dissemination mechanism and their relative contribution to information shared

Category	**Description**	**Information Dissemination**	**Movement to the next stage due to**
Unaware	Population that is unaware of the existence of the disease	none	Media-shared information; person-to-person shared information
Aware	People who are aware of the existence of the disease but do are not alarmed	0,05	Susceptibility Assessment
Actively Aware	People who are aware and actively concerned. Assumed to actively interact and disseminate information	0,80	Fatigue. People assumed to get tired but how fast this happens is controlled by Severity Assessment
Fatigued	People experiencing "information fatigue" after being Actively Aware.	0,05	Recovery Rate over time
Recovered	People who are Aware after having "recovered" but are not currently Active	0,10	Become Active after recovery due to Susceptibility Assessment. People here more "resistant" the first time they became Active.

Relative Contribution of each mechanism

The relative contribution of each of the described mechanisms is challenging to assess. We have decided to prioritise Observations, followed by the Top Down message distributed by authorities, and lastly by the Bottom Up message disseminated directly between individuals (see Table 12).

Moreover, this relative contribution might not be a static process, as the constant values here represent, but a dynamic one, especially in the relative contribution of Top-Down versus Bottom-Up messages. Trust in authorities might play a significant role (Siegrist & Zingg, 2014) and the Trust and Confidence model postulates that it has an important role in threat management as it "is believed as the main core of hearing, interpreting, and responding to public health messages" (Khosravi, 2020, p. 1). We have decided to exclude this possible influence of trust as, evidence suggest high levels of trust in authorities for the Norwegian population during the COVID-19 (Ivarsflaten et al., 2020).

Table 12: Relative Contribution of drivers of Threat & Efficacy Appraisals

Contributors	**Value (weight)**
Contribution of Observations on Threat Appraisals = Contribution of Observations on Efficacy Appraisals	50%
Contribution of Top Down message on Efficacy Appraisals = Contribution of Top Down message on Efficacy Appraisals	30%
Contribution of Bottom Up message on Efficacy Appraisals = Contribution of Bottom Up message on Efficacy Appraisals	20%

Drivers of Perceived Costs of the Prophylactic Behaviour

Not least, the Perceived Costs of a Prophylactic behaviour are also conceptualised as emanating from three different mechanisms. Janis and Mann (1977) have suggested that gains or losses (costs) can be categorised into four major types: (a) utilitarian gains or losses for self, (b) utilitarian gains or losses for significant others, (c) approval or disapproval from significant others, and (d) self-approval or self-disapproval (in Prochaska et al., 1994, p. 40). While, here, we do not differentiate between costs for the self and for others, we represent both utilitarian costs, and the suggested approval or disapproval from significant others (which we term the Social Costs).

Livelihood Costs & Ease of Engagement Costs

The first type of costs are "practical" costs. *Livelihood Costs* is a term here used to represent broadly costs of Social Isolation that can impact the livelihood of individuals as for example the loss of job and income, (especially if coupled with lack of financial support), need to leave the house for groceries or other obligations, unavailability of online or any other solutions that allow the individual to stay at home etc. Governments and other institutions are crucial in reducing those costs for the individuals. In the case of the Level of Adoption of Hygiene Behaviour, similarly significant costs are those of the *Ease*

of Engagement in Hygienic Behaviour. This ease can represent the availability and ease by which the individual can engage in relevant hygienic behaviour, from the broad availability of water and soap, disinfectants, masks, or any other solutions in place that can ensure that the individual can easily follow hygienic proposals[4].

Some evidence of such mechanisms for the case of Social Distancing during the COVID-19 crisis come from a review of new evidence by Webster et al (2020) who found two of the reviewed studies explicitly reporting the loss of income and need to work as significant reasons to not comply with quarantine instructions (DiGiovanni, Conley, Chiu, & Zaborski, 2004; Teh et al., 2012). This is, of course, rather intuitive and is mirrored in studies that attempt to quantify effects of specific measures on the mobility of the population (e.g. Abouk & Heydari, 2020; Askitas, Tatsiramos, & Verheyden, 2020): school and workplace closures, for example, can easily be considered as reducing the *Livelihood Costs* of "leaving the house".

Social Costs

Decision making depends on our perceptions of how others might judge our behaviour (Milinski, Semmann, & Krambeck, 2002). Costs related to the behaviour of what others are expected to also have an influence on our own behaviour and imitation of others' behaviour has been present in epidemiological models (Chang et al., 2020; Poletti et al., 2011b, 2009). Some of the Health Behaviour theories explicitly incorporate the notion of "(Social) Norms" existing in the person's environment and influencing their behaviour. It is reasonable to assume that individuals do look around them to determine what the Social Costs of a behaviour are. The assumption we use here can be described as following: Individuals look at the average adoption of the proposed behaviour (mobility reduction or other hygiene behaviour). If others are adopting the behaviour, it is not "costly" for the individual to do so as well; rather it is costly socially to *not* do so. In the same way, when others do *not* adopt the behaviour: the person might also feel pressured to not adopt the behaviour either for fear of criticism or of simply "being different".

Fatigue

Emotional reactions, particularly boredom and loneliness have also been reported as reasons to not adhere with quarantine (DiGiovanni et al., 2004). Individuals' costs of maintaining the behaviour are expected to increase the more time of practicing the behaviour passes: people simply get tired to be at home or people get tired of extensively washing their hands. A similar mechanism of "isolation fatigue"

[4] The two mechanisms represent the same process, however we have decided to use different terms that lead to a different "directionality" of the costs and their relationship with the behaviour. We perceive the term Livelihood Costs to be a little more intuitive in terms of its real-world meaning that a term such as Ease of Engagement with Social Isolation.

was incorporated in the SD model developed by J. Homer (2020). We do not expect fatigue to have a one-on-one, linear relationship with the recent intensity of the prophylactic behaviour, however this is an assumption that should be further explored. In the case of Social Isolation, we expect this fatigue to be translated to a higher cost than in the case of hygienic behaviour as the former is a more "intense" behaviour that directly impacts important social interactions with others and as such can be expected to have higher costs (see Fig 24).

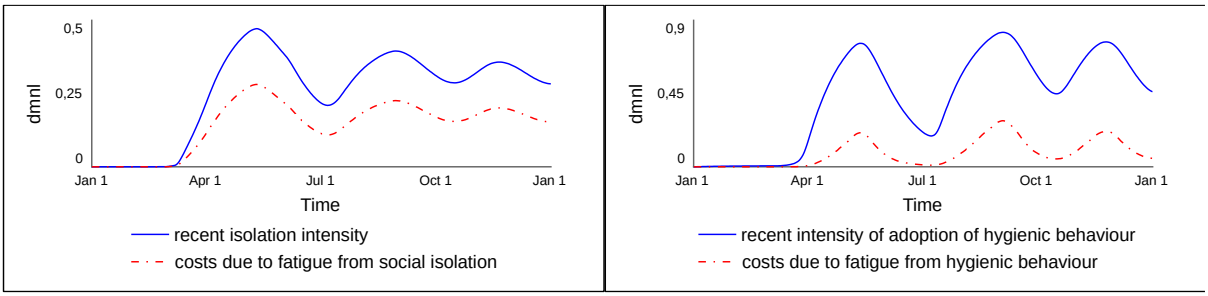


Figure 24: the hypothesised relationship between recent intensity of prophylactic behaviour and costs of fatigue due to engagement with said behaviour

Relative Contribution of each mechanism

The relative contribution of the Cost mechanisms is also a rather challenging assessment. We have decided to prioritise the "practical" costs (Livelihood Costs or Ease of Engagement with Hygienic Behaviour), followed by Fatigue, and lastly by the Social Costs (see Table XXX).

Table 13: Relative Contribution of drivers of Costs of Prophylactic Behaviour

Contributors	**Value (weight)**
weight of livelihood costs = weight of ease of engagement with hygienic behaviour	60%
weight of fatigue from distancing = weight of fatigue from hygienic behaviour	24%
weight of social costs for mobility = weight of social costs for hygienic behaviour	16%

Partial Testing of Behaviour Model

We will briefly perform a partial testing of the proposed structure to see how it fairs over the reference period (January 1st to June 1st). The model will run using data of reported Daily New Infections, New Hospitalisations and Critical Care admissions, as well as New Deaths. The main assumptions and data used for the partial testing of the main Infection model are presented hereafter.

Governmental Message & the Additional Top-Down Communication SWITCH

As described above, we have endogenized (and grounded on the actual cases) the governmental decision regarding their communication of Threat and Efficacy. COVID-19 is however not a local phenomenon and governments' reactions were not only informed by local information. Norway had its first case later than other European countries and after evidence had accumulated regarding the seriousness of the disease, so Top-Down communication might have been initiated earlier. To investigate this, we can look at the timeline of some communication messages (Table 14) and present our assumption on how those messages translate to a value for the *Top Down Threat Related communication message*, which we will compare with the endogenous, model-produced message (Figures 25 and 26).

Table 14: Timeline regarding Communication of Top-Down message by Norwegian authorities

11.02	**26.02**	**12.03**	**07.05**
Norwegian Health Institute (FHI) publishes *Facts about COVID-19*	First case announced in Norway - FHI publishes *Risk Assessment for Norway*	WHO characterises COVID-19 a pandemic - Norway announces measures - First death in Norway	Government announces gradual reopening

We hypothesise that each of the above messages translate to a Threat-Related communication increase. We do not operationalise those messages as "spikes" due to both the presence of many more messages and the, exogenous to our model, reproduction and amplification of governmental messages from news sources. Instead, we perceive them as raising the level of the overall communication message. The endogenous message, as guided by the non-linear *effect of new cases on governments communication message magnitude* is presented in Figure 25 together with our assumptions.

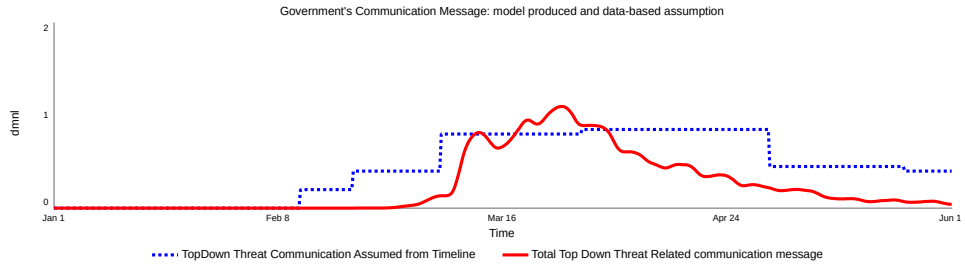


Figure 25: Top-Down Threat Communication as assumed from communications Timeline and endogenous Top-Down Communication of Threat

We do observe a significant delay which is to be expected due to a logical "sensitivity" of governmental decision-making to the possible threat posed by Covid-19[5]. This delay in the governmental response

[5] This «sensitivity» would not be expected, for example in China or in Italy which was earlier hit by Covid-19.

guides us to include an Additional Top-Down Communication mechanism that is very sensitive to information on first local cases. With this addition, the governmental communication message approaches better our timeline assumptions (Fig. 26).

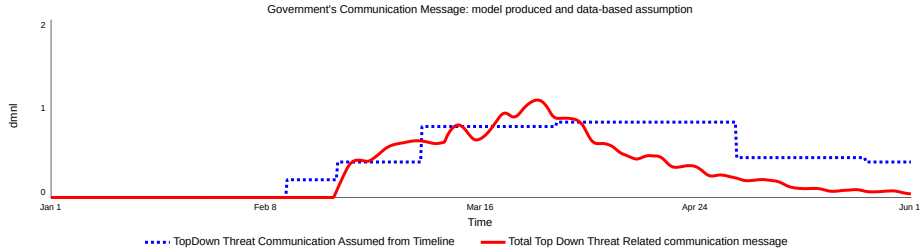


Figure 26: Top-Down Threat Communication as assumed from communications Timeline and endogenous Top-Down Communication of Threat with Additional Top-Down Communication mechanism

We, moreover, hypothesise that the Efficacy-Related communication message has a higher intensity that the Threat-Related one, as we believe this to be true for the case of Norway: information and communication by governmental agencies did emphasise the measures and their efficiency in fighting the spread of Covid-19. We choose a 15% higher intensity of Efficacy relative to that of the Threat.

However, we introduce a very small delay in the communication of Efficacy relative to that of the Threat to account for some "lag" between the two types of messages due to perhaps lack of knowledge or other uncertainties related to the response efficacy. To summarise, the baseline scenario has the following assumptions regarding the Top-Down communication message

Table 15: Top-Down Communication message-related Assumptions for Baseline Scenario & Partial Model Testing

Parameter	**Value**
ADDITIONAL TOP DOWN THREAT COMMUNICATION SWITCH	1 (ON)
ADDITIONAL TOP DOWN EFFICACY COMMUNICATION SWITCH	1 (ON)
intensity of Efficacy Related communication	1,15
intensity of Threat Related communication	1
Delay in Efficacy communication relative to Threat communication	4 days

Costs

We have also had to make some assumptions regarding "practical" costs of both prophylactic behaviours under consideration. Both Livelihood Costs (relevant for Social Isolation) and Ease of Engagement in Hygienic Behaviour were developed based on the observed situation in Norway.

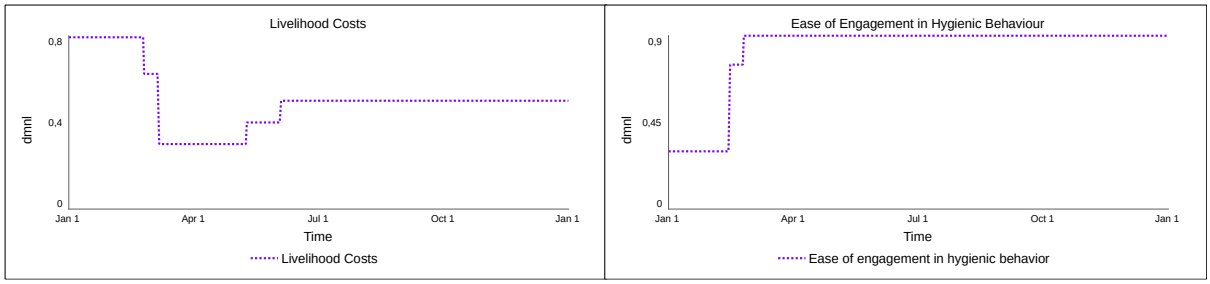


Figure 27: Livelihood Costs and Ease oh Engagement in Hygienic Behaviour – assumed

In terms of the other two types of costs, our assumptions are that the *time to perceive the behaviour of others* which makes individuals evaluate the Social Costs is equal to 7 days, and the *time to update the perception of recent isolation* or *recent hygienic behaviour intensity* that allows people to evaluate how "tired" they might be from practicing the behaviour is equal to 30 days.

Results

The results of the partial testing of the behavioural model compare well with the data on mobility. We present, in Figure 26, both data from the Institute for Health Metrics and Evaluation (IHME, 2020) and from Google (2020), although we have used the former to normalise our model. We do observe a slow initial response which is to be expected due to the absence of more "global" information that would be expected to have already been operating before the Norway-specific response (increasing the perceptions related to Threat and Efficacy, as well as the overall communication mechanisms both Top Down and Bottom Up).

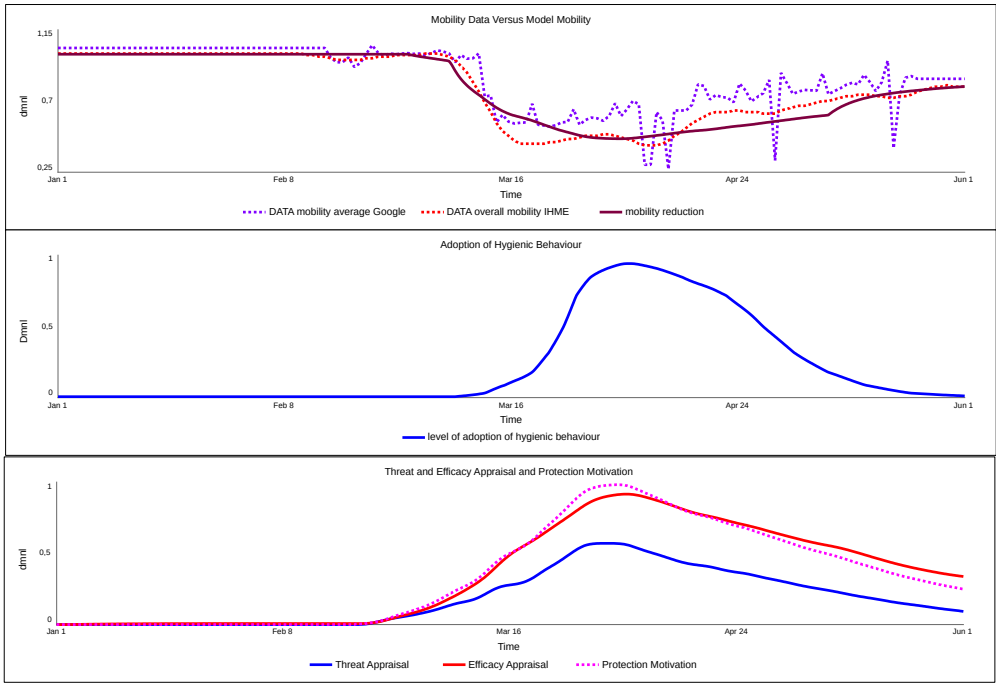


Figure 28: Partial Model Testing of Behavioural Model: Mobility Reduction Compared to data, Adoption of Hygienic Behaviour, and Threat, Efficacy and Protection Motivation over the reference period

In terms of the fit with the data collected by Ivarsflaten et al. (2020) and reported by Sætrevik (2020) on the perceptions of Norwegian citizens between 20 and 29 of March 2020, the model approaches quite well the observed values, although the introduction of some perception and communication delays in our model leads to the observed values being reaches a little later (see Figure 29)

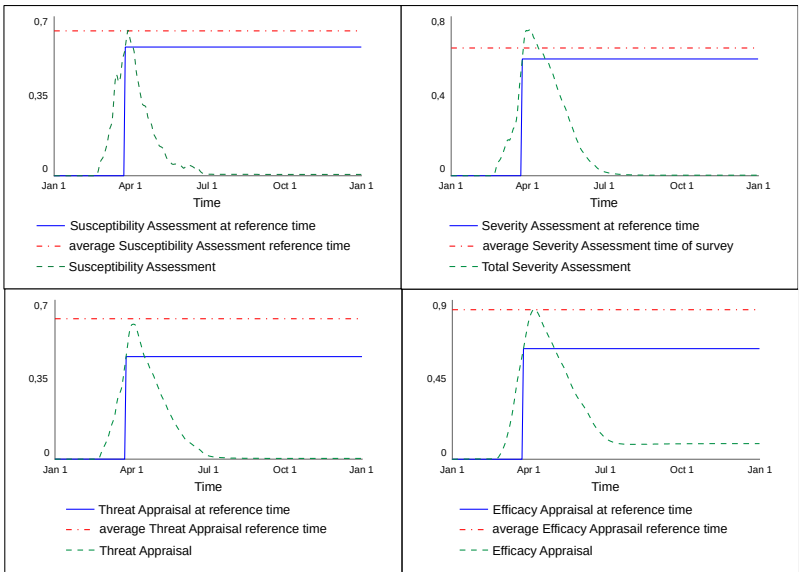


Figure 29: Partial Model Testing of Behavioural model: Blue lines indicate the value of the variable at the reference time, red lines the value at the reference time according the data, and green lines show the behaviour over time of the variable

Some comments on the Theory & Assumptions

Before continuing, we find important to answer some questions related to the assumptions of the model

Is this really where Efficacy Appraisal comes from?

We do not know for sure. Self-Efficacy has received a lot of attention in the psychological literature, however, Response Efficacy is not equally well-defined. We have presented our assumptions with Efficacy building up similarly to Threat, however, due to its significance, further iterations need to find better ways of establishing the drivers of Efficacy Appraisal through additional literature review or primary data collection.

Is the Social Costs mechanism so weak in reality?

Probably not. The relative contribution of the social costs on the total costs of a prophylactic behaviour (weight of social costs) is assumed to be 16%. The Social costs activate a "resistance" loop at the early stages of the epidemic (R5) slowing down prophylactic responses and are, as such, very significant. They might very well be stronger, but this is difficult to assess without introducing the effects of global information that would be expected to raise both governmental and local appraisals regarding Covid-19. Hence, the data we have and the model-produced behaviour cannot help us clarify the strength of this mechanism: additional research in the relevant literature is necessary.

Do people update their assessments / appraisals that quickly?

Not likely. Perceptions do not, in reality update as quickly as represented here. We have chosen shorter delays or completely omitted a smoothing process on the updating of some perceptions due to two reasons: a) Government's communication message is delayed in relation to observed data due to the need to endogenise this decision, b) the population themselves is expected to have already started updating relative perceptions due to the global situation and, even more, the situation in neighbouring countries (Engle, Stromme, & Zhou, 2020) which are not described in the model. For application in cases such as China, or Italy, much larger delays should be utilised.

Are there more diffusion mechanisms?

Most certainly yes. People do not have global information of the behaviour of others as easily available as represented here. Network effects are very significant and should be further incorporated.

Chapter 4: Analysis of the Simulation Model

"Modelling, as a part of the learning process, is iterative, a continual process of formulating hypotheses, testing, and revision, of both formal and mental models"

(Sterman, 2000, p. 83)

Validation

The process of validating a SD model is both built into its development and an iterative, gradual process which aims to build confidence in the simulation model (Forrester & Senge, 1980). To build such a confidence, the modeler seeks to demonstrate that "both the structure and behavior of the model correspond to existing knowledge about the system under investigation" (Homer, 2012, p. 282). Yaman Barlas (1996) proposes a "logical order" of tests that can assist the modeler in their attempt to validate their model and this is the order that we will also follow here.

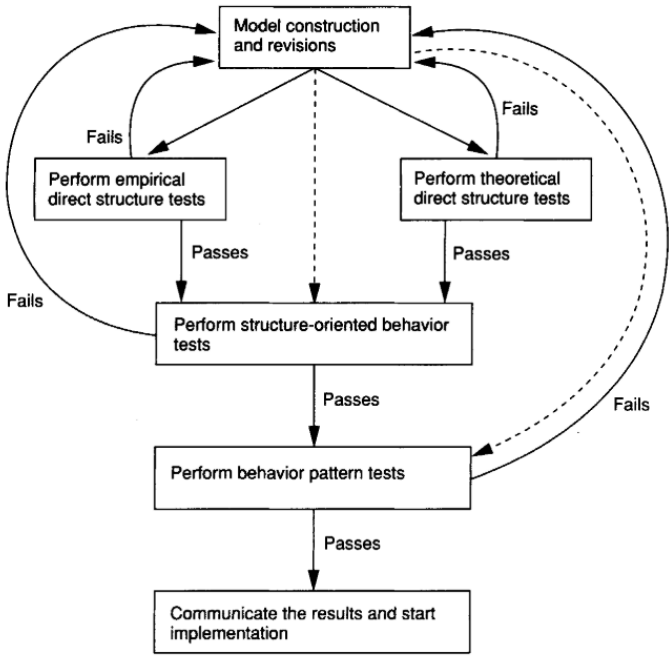


Figure 30: Logical Sequence of Formal Steps or Model Validation (Barlas, 1996, p.194)

1. Direct structure tests
2. Structure-oriented behavior tests.
3. Behavior pattern test

Direct Structure Tests

Examples of direct structure tests proposed by Forrester and Senge (1980) are structure and parameter verification tests, direct extreme-conditions test and dimensional consistency test.

Structure Verification Test

Structure Verification test describes the process by which the model is compared with the structure of the system in question and "[t]o pass the structure-verification test, the model structure must not contradict knowledge about the structure of the real system" (Forrester & Senge, 1980, p. 212). Theoretical Structure Verification test, as compared to Empirical, involve the comparison of the model structure with knowledge about the system as it exists in the literature (Barlas, 1996), and it is this type of testing that we have performed throughout the development of the model. The grounding of the structural components to existing literature is presented in more detail under the relevant sections of this thesis, as well as further described in the model documentation.

Parameter Verification Test

Parameter Verification refers to the evaluation of constant parameters in relation to knowledge of the real systems. Forrester & Senge (1980) discuss both Conceptual Correspondence (whether parameters match elements of the structure of the system) and Numerical Verification (whether the value of the parameter "falls within a plausible range of values" for the actual parameter (p. 213)). In the case of the Infection Model, detailed conceptual and numerical verification are presented in the description of the model and in the documentation. Both empirical and modeling studies have been reviewed and values for parameters that corresponds to this range were chosen. It is very important to note however two elements: firstly, many of the parameter values identified in the literature come from modeling studies. Modeling studies make parameter estimates, to some extent at least, based on optimisation to match the behaviour of the real system. As such, parameter values are linked to the structural components of the system: a parameter value that "fits" the fundamental SEIR model would need to be adapted to fit our adopted SEIR model. That is of course not to say that this allows us to deviate very significantly from the range of values we see in the literature and especially through emperical studies, however, the described in the literature values need always to further tested through behaviour testing (see below). The second element regarding parameter verification of the infection model is, as expected, the high degree of uncertainty regarding numerical values of COVID-19 related parameters. As our knowledge grows, parameter verification tests will need to be performed again and eventual inconcistencies addressed in further iterations of the model.

With regards to the Behavioural model, Numerical Verification is particularly hard, especially since the specific case study is describing a phenomenon that cannot easily be compared to other experiences. As such, Structure-Oriented Behaviour tests, to be described in the next section, are necessary to assist us in understanding which parameters are "significant" enough to require further exploration. In terms of Conceptual Correspondance, we are confident, through our literature review, that the parameters described in the model match elements of the real system, as it is at least reflected in our understanding of it.

Direct Extreme Conditions Test

The Direct Extreme Conditions Test is an assessment of all the equations of the model so that they are robust under extreme conditions. Each equation has been inspected to ensure it responds adequately to extreme inputs. Wherever appropriate, MIN or MAX functions have been employed to not allow the equations to take unreasonable values and the upper and lower bounds of table functions were estimated to ensure that values remain reasonable under extreme conditions.

Dimensional Consistency Test

All variables and parameters of a simulation model have assigned units of measurement and, for the model to be considered valid, those need to be consistent "*without the inclusion of arbitrary scaling factors that have no real world meaning*" (Sterman, 2000, p. 866, emphasis in original). The simulation software we used (Stella Architect 2.0) performs this test automatically and we have not included parameters with no real-world meaning (see Appendix 3)

Boundary Adequacy Test

This test "asks whether or not model aggregation is appropriate and if a model includes all relevant structure" (Forrester & Senge, 1980, p. 215). To determine this, in terms of the included structure, the purpose of the model is the most important question. We have already described that the purpose of this model is not to suggest policies for the management of Covid-19 but, rather to attempt to provide an endogenous view of the population's response that might assist in the conversation around management of such environmental Threats. As such, the boundary for the main Infection model is determined to be adequate: this model acts as the "engine" on which to test the structural proposal of a modified SEIR model and, even more so, on which to ground the response of the population. The Behavioural model is here considered as a first iteration on the attempt to bring together theoretical models and knowledge of the population's response to an environmental with a focus on communication messages that can help elicit a more favourable response. We are confident with the boundaries of the model in its first iteration, and the boundary test will need to be re-examined if the model is further developed to propose policies on communication strategies.

Structure-Oriented Behaviour Tests (Indirect Structure Tests)

Indirect Extreme Conditions Test

This test is performed to evaluate whether the equations of our model give rise to plausible behaviour under extreme conditions. Indirect Extreme Conditions test utilises simulation for this evaluation. A very fundamental test would be to see what would happen if no COVID-19 case was ever imported to Norway. The expected behaviour of the system would be that there are none infected and that there is

no response by the population. The fomer is true, as can be seen in in the graph of Daily New Cases which remains at 0 (Figure 31).

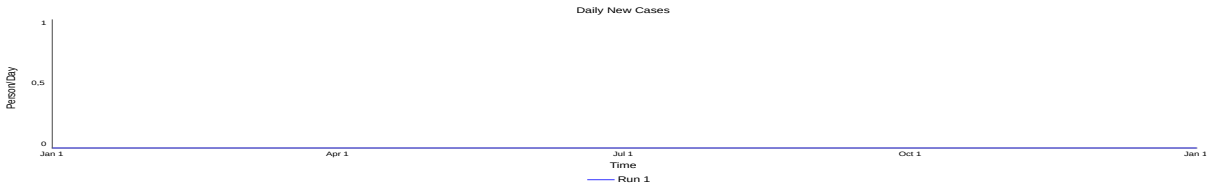


Figure 31: Daily New Cases under testing with Zero Imported Cases

The latter is *not* true: we still observe awareness regarding COVID-10 spreading in the population (see Figure 32)

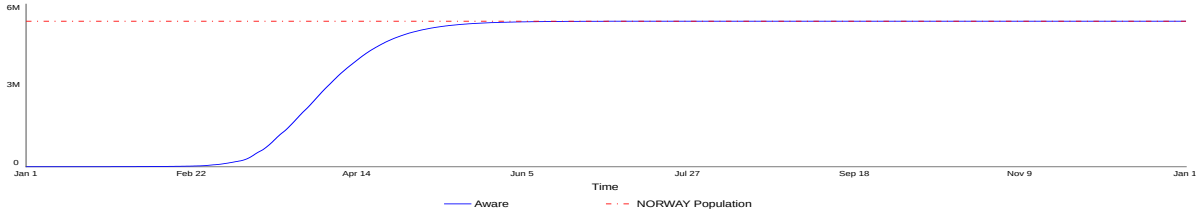


Figure 32: Aware Population and Total Population of Norway under testing with Zero Imported Cases

Those results are not surprising. In the case of the Awareness structure, the exogenous input *COVID-19 mentions in local news sources* is still operating, raising awareness in the population: since the media still spread information about the (now non-existent) virus, people become aware of it. This is not unreasonable if we consider that the population has become aware of other instances or virus that never actually reached the country. We see however an additional important confirmation: the population remains in the Aware state and never becomes Actively Aware since the Susceptibility Assessment remains at 0 (there are no cases, hence there is no perception that one can become infected). By nullifying the exogenous mentions via media, we indeed see that no one ever becomes Aware of COVID-19 (Figure 33)

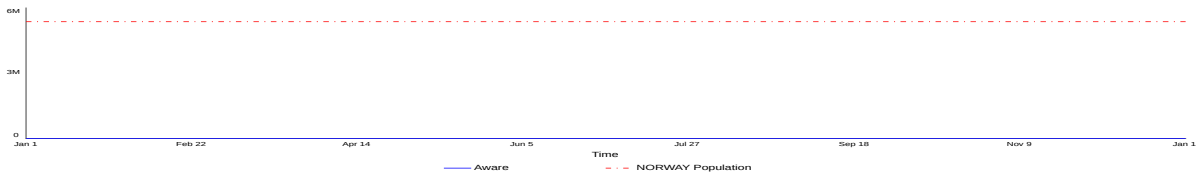


Figure 33: Aware Population and Total Norwegian Population under testing with Zero Imported Cases and with Zero News Media Coverage of COVID-19

There is another behaviour that might initially be seen as not reflecting how the population would respond in the absence of any local case and that is in the behaviour of *mobility reduction*. There is, in

this case as well, an exogenous parameter that justifies a reduction in mobility even in the absence of the virus, namely the *Livelihood Costs* (see Figure 34)

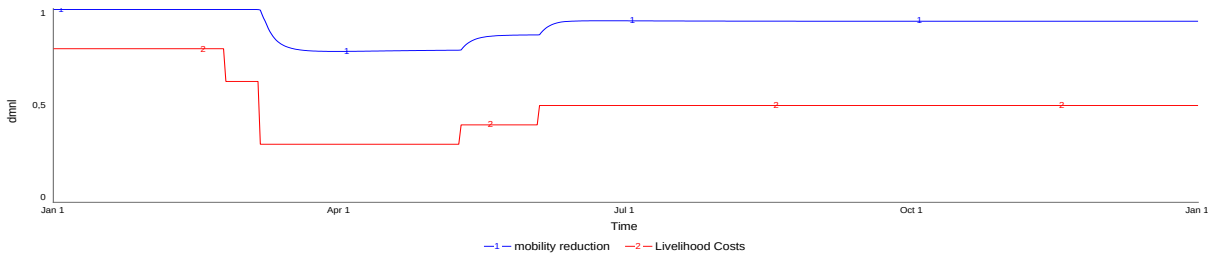


Figure 34: Mobility Reduction and Livelihood Costs under testing with Zero Imported Cases

The exogenous decrease in Livelihood Costs, makes it so that the population, even with zero *Protection Motivation* against COVID-19, reduces their mobility (by a maximum of 22% reduction). It can be argued that this is rather reasonable: if the costs of staying home are reduced, people would choose to some extent to remain at home (if, for example, I can work from home and face no cost to not physically go to my workplace, I would chose to reduce my mobility to some degree). To test the model, we will set the Livelihood Costs equal to their initial value and, sure enough, we can observe no reduction in mobility (Figure 35)

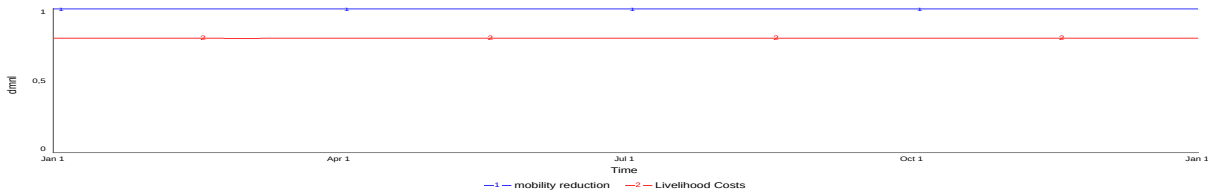


Figure 35: Mobility Reduction and Livelihood Costs under testing with Zero Imported Cases and Livelihood Costs equal to baseline

Another significant extreme condition test we should perform would be the response of the system if no Testing Capacity was ever acquired. The system responds adequately, in that there are zero *Cumulative Positive Tests* (Figure 35).

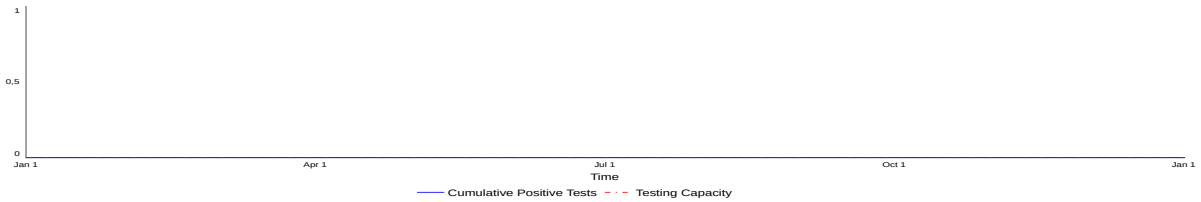


Figure 36: Cumulative Positive Tests and Testing Capacity under testing with Zero daily additions in Testing Capacity

The behavioural structure responds in exactly the same way as in the previous test where there were zero Daily New Cases.

Behaviour Sensitivity Test

This test "consists of determining those parameters to which the model is highly sensitive, and asking if the real system would exhibit similar high sensitivity to the corresponding parameters" (Barlas, 1996, p. 191). As such, parameters in this model are expected to largely fall under three categories: those that are *expected to be sensitive*, those that represent leverage points for policy suggestions and, as such, *should be sensitive*, and those that *should not* be sensitive. The focus of the sensitivity test is, of course, the latter category. Sensitivity testing in this case aims to assist us not only in the validation of this iteration of the model but to also provide us valuable insights on which parameters we need to look further into through further data collection for their quantification.

Very briefly, parameters of the main infection model are all expected to be sensitive to a smaller or larger extent (e.g. duration of infection or of residence in each of the severity stocks, fractions of infected at each of the severity categories and, of course, absolute and relative infectivity). The tremendous focus of research efforts to quantify such parameters can convince one of their significance, and further versions of this model should be in line with state-of-the-art information on the range of such parameters.

The parameters of the Testing module represent decision rules of the government: how much testing do we perform and who do we test? Those decisions interact with the direct mobility reduction due to infection that we have explored in the Infectivity sector of the Main Infection model so as, the more people we test, the more people are quarantined. Since we already consider that Hospitalised and Critical Care infected will have much lower contacts anyway (tested or no tested), and since the numbers of those patients are in any case low, the Target Test rates for the two severe categories are rather insensitive to changes. The Target Test Rate for the Tested and for Symptomatic Infected however is, as expected, sensitive and this sensitivity is higher when the Contact Tracing Mechanism is active, as well as when the behaviour is endogenised (more tests lead to more response by the population). The intensity of the Contact Tracing Mechanism as well as the overall Testing Capacity are, as expected, very sensitive to changes.

In terms of the direct contacts reduction as a result of quarantine, we experiment with a relatively wide range of values for the *fractional contacts adjustment* for the symptomatic population and see that, in fact, it does lead to a higher first wave. Interestingly, the second wave is better managed due to the behavioural response that is maintained by the population

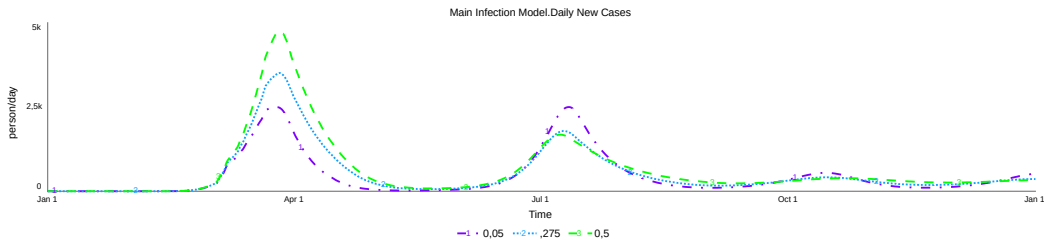


Figure 37: Daily New Cases for different values of the fractional contacts adjustment for the symptomatic population

The main focus of the Sensitivity analysis is the Behavioural model due to the very large uncertainty of the parameters and that fact that it represents the main focus of our work. We have performed a detailed sensitivity analysis (see APPENDIX 2) and, as expected, have identified a number of parameters that are sensitive. Our model is very clearly a first iteration in the representation of the theoretical constructs discussed above, and as such, this test aims mainly to direct us in which parameters and relationships we will need to be focused due to the large impact of their system. One such very interesting parameter is on the effect of the intensity by which we isolate on the costs of isolation (represented in the non-linear effect *costs due to fatigue from social isolation*, see Fig 38)

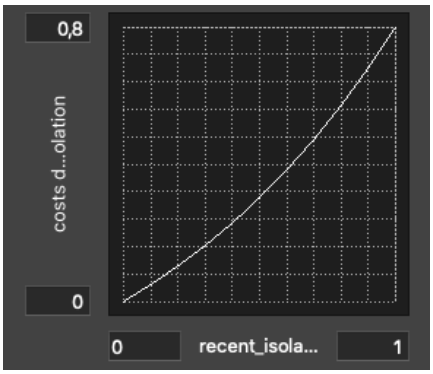
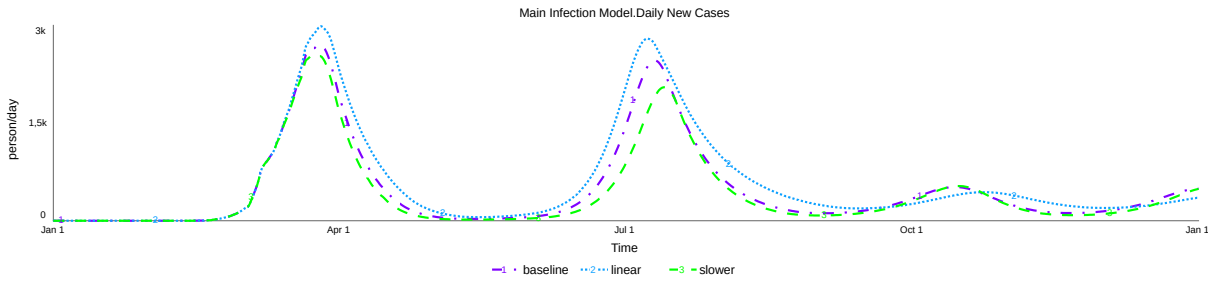


Figure 38: costs due to fatigue from social isolation: the assumed nonlinear relationship between the recent intensity of social isolation and the costs of this behaviour

We have experimented with both a linear relationship and a "slower" response, and we see that it does effect both the magnitude of the infection waves and the speed at which the second wave is observed. As such, it would be very beneficial to estimate how fatigue might translate to costs, as well as what we can do to reach a more favourable shape. The behavioural pattern in the same and this applies for all the sensitive parameters in the Behavioural Model, except the practical costs of the behaviour (*livelihood costs* and *ease of engagement with prophylactic behaviour*) that are expected to have a very large impact on whether people actually comply with the advice that can slow down the infection



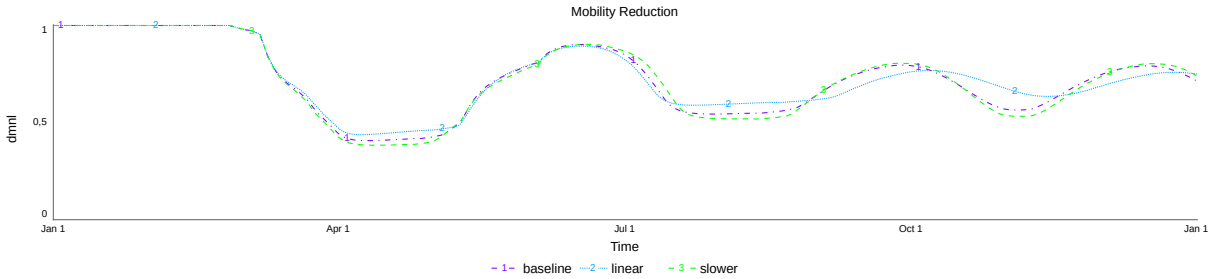


Figure 39: Daily New Cases & Mobility Reduction for different shapes of the effect of fatigue on costs of Social Isolation

Behaviour Pattern Tests

This category of tests aims to compare the behaviour of the model with a reference model of behaviour, when available.

Partial Model Testing

Partial Model Testing "involves simulating the behavior of a functional component of the model, which may be as small as a single equation, in response to empirical input data for comparison with empirical output data" (Homer, 2012, p. 282). In this type of testing, a part of the model is being isolated (the loops that connect it with the rest of the model are "cut") and an exogenous input takes the place of the cut-off structure. We have presented the results of Partial Model Testing for both the Main Infection and the Behavioural model and are rather confident in their fit well with the available data. We would like however to test a structure for which we don have available data for and that is the Top-Down information dissemination structure. We do not have a measure of the actual rate of information sharing for the case of Norway however since we have normalised this mechanism and assumed its contribution to be given as relative to the reference period, the values are not important. What is important is the behavioural pattern and evidence suggests that information sharing precedes spikes on infections (Singh et al., 2020). According to data provided by Alshaabi et al. (2020), the first peak of the information curves occurred in most countries before the observed 10th infection in the country (see Fig 40). Moreover, a second wave of information has been observed and is very closely related to the 10th observed death.

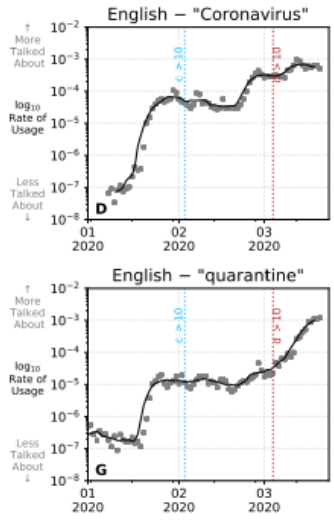


Figure 40: Time series for caseloads and death counts for the United States, and 1-grams for 'Coronavirus' & 'quarantine' in English. Figure 4 in Alshaabi et al. (2020). Blue lines represent the 10th case and red the 10th death for US

Due to the lack of global information, our model's behaviour is somewhat slower than what is indicated from such data and we either underestimate the second peak or overestimate the first one (see Fig 41). The uncertainty around this mechanism we perceive to be somewhat tolerated due to its assumed low contribution on both Threat and Efficacy Appraisals (20% of the total 100 %), however additional data and structural information can help us reach better estimates at further iterations of the model.

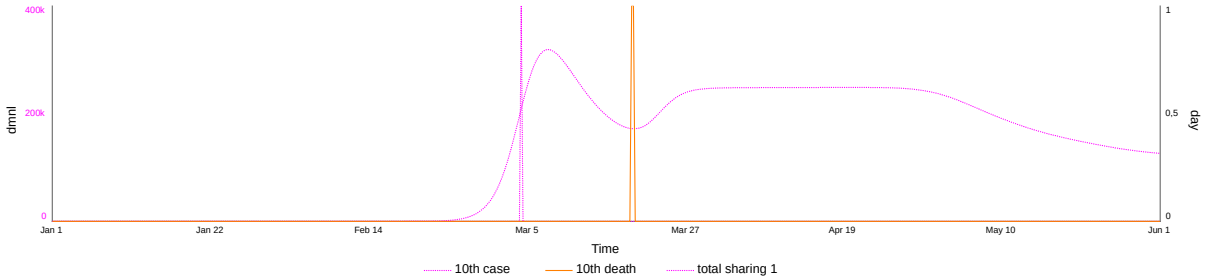


Figure 41: Model Produced total sharing via the Bottom Up mechanism compared to the 10th case and 10th death in Norway

Full Model Behaviour Tests

Such tests aim to measure whether and with what accuracy the model can reproduce the reference model of behaviour. The emphasis of such tests are in predicting the major patterns of the behaviour exhibited in the real system and not to produce a "point-by-point" prediction (Barlas, 1996, pp. 192–193). We will present in more detail the results of such tests in the following section.

Validation Overview

The validation process makes us relatively confident in our model. We perceive the structural validity to be rather high. Despite many rather uncertain parameter values and the lack of data for both

parameterisation and behavioural validation, we observe a lack of sensitivity for many parameters. Most, importantly, the validation process has been crucial in our understanding of which values and mechanisms we need to focus our efforts on for further iterations of the model.

Results of the Full-Model

Baseline Scenario

For the full model results, we run our model for 365, from January 1st, 2020 to January 1st, 2021. The values for the parameters are those presented so far and the values for sensitive parameters can be found in Appendix 1.

Results

The full model seems to match the behavioural pattern of the observed data, however there is a relative overestimation of tests and deaths for the reference period (see Figure 42). Despite contact tracing, the model produces an additional, second infection spike that is supposedly currently underway (July 2010). This is not very worrisome in terms of our model as we are aware of its limitations both in information regarding the testing and contact tracing mechanism as well as the uncertainty around the actual risk reduction effects of hygienic measures, and, of course, the level of aggregation (every person in Norway has exactly the same probability to come to contact with an infected). What is worrisome, in terms of Covid-19, is that there *is* a second spike and our model predicts what is termed the "Hammer and the Dance" (Pueyo, 2020): large infection wave(s) followed by smaller waves until vaccines are developed.

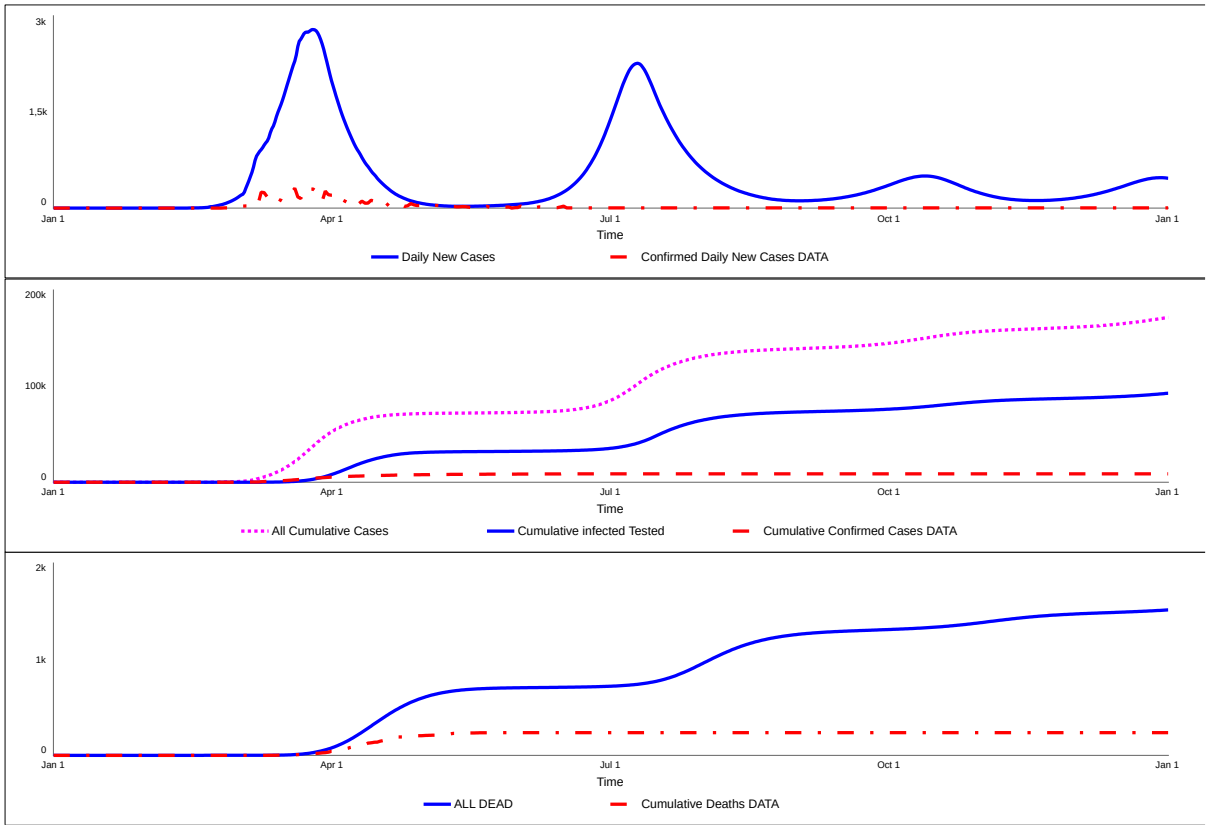


Figure 42: Full Model, Baseline Scenario: Daily New Covid-19 Cases, Cumulative Tested Infected, and Cumulative Deaths

This overestimation of deaths and tests emanates from an overestimation of the Hospitalised and Critical Care Infected (see Figure 43). Those are the two severity categories that we perform prioritised testing on and the two categories from which people can die due to Covid-19 infection. Why this overestimation then?

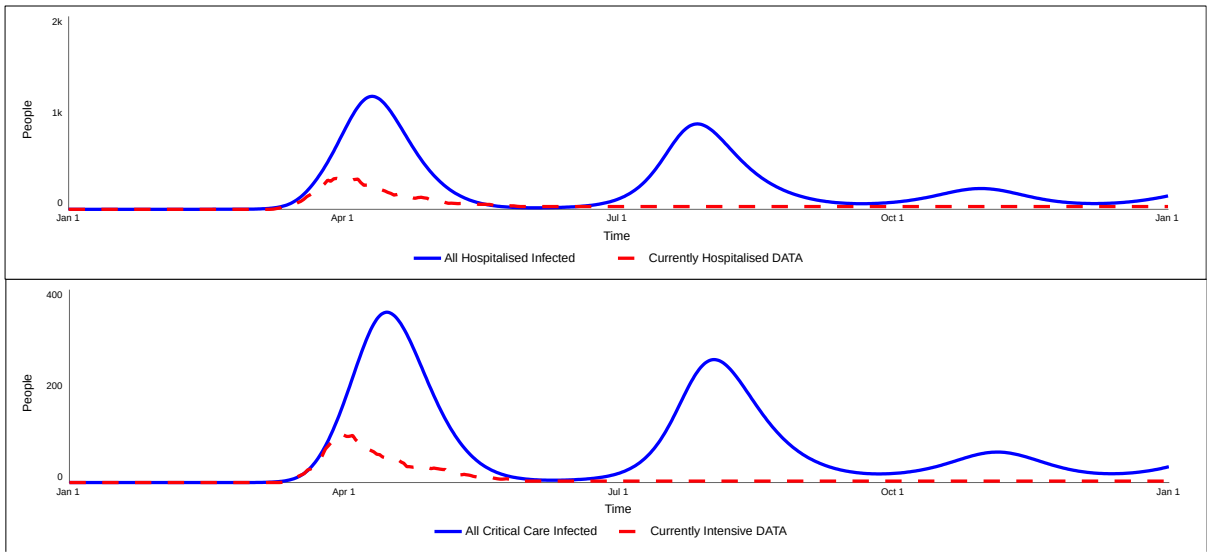


Figure 43: Full Model, Baseline Scenario: All Hospitalised and Critical Care Infected

Looking at the behavioural model for the source of the overestimation, we do observe that the response of the population, as produced by the model, is less steep than the one observed in the data for mobility over the reference period. Specifically, our model produces a slower response until the beginning of April, when it "catches up" with the data and, thereof, the mobility of the population recovers almost equally delayed relative to the actual observations. A delay is to be expected; we have discussed already that perceptions of Threat and Efficacy and relative Top Down and Bottom Up communications are expected to have begun to build up earlier that what we here represent due to globally available information and prevalence of the virus. As one could predict from the infection data above, a "return to normality" is not feasible according to our model: the response of the population (as *mobility reduction* and *engagement with hygienic behaviour*) will need to be employed time and time again to combat subsequent waves and, if we don't want results that are worse than the presented above, it seems we cannot fully return to our prior-to-Covid-19 behavioural patterns.

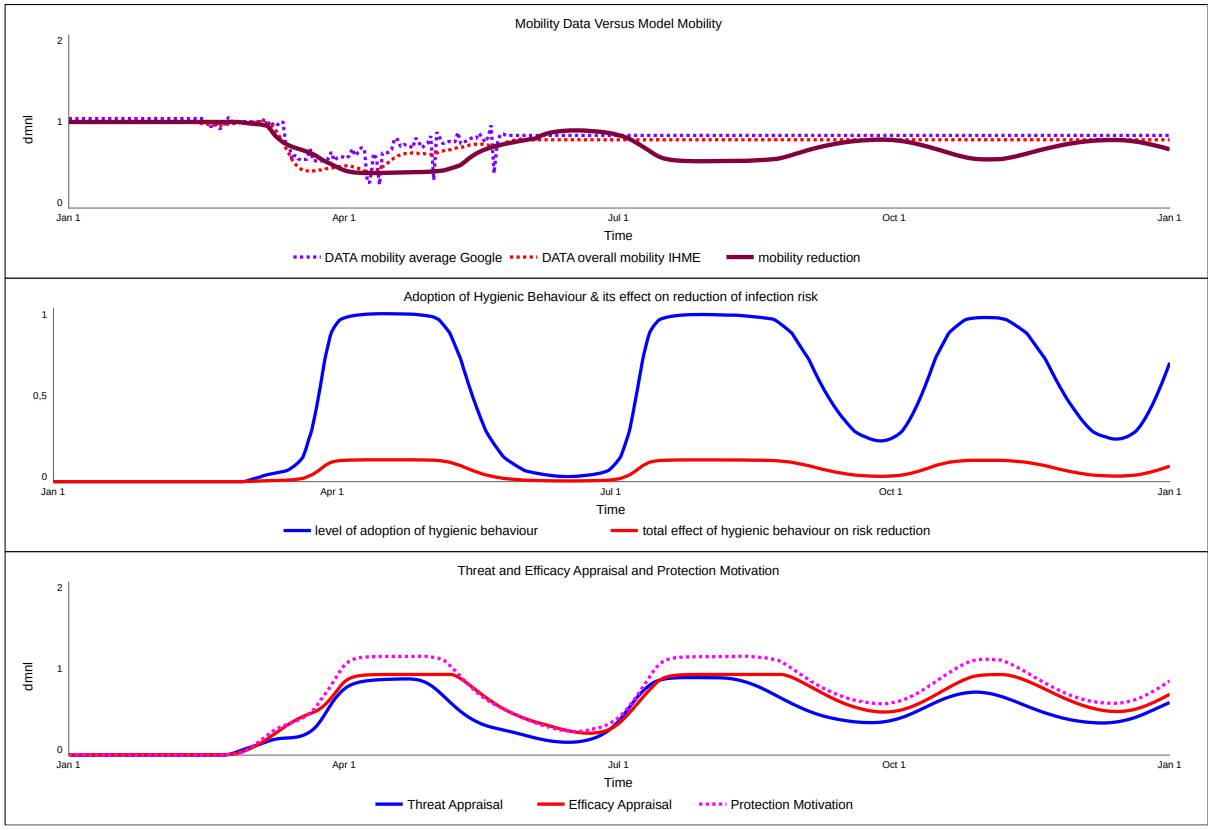


Figure 44: : Full Model, Baseline Scenario: Population Mobility, Engagement with hygienic Behaviour, and Threat and Efficacy Appraisals and Protection Motivation

To understand better where those dynamics come from, we will look at the feedback loops that guide the system and how the give rise to the behaviour presented above.

The Feedback Story

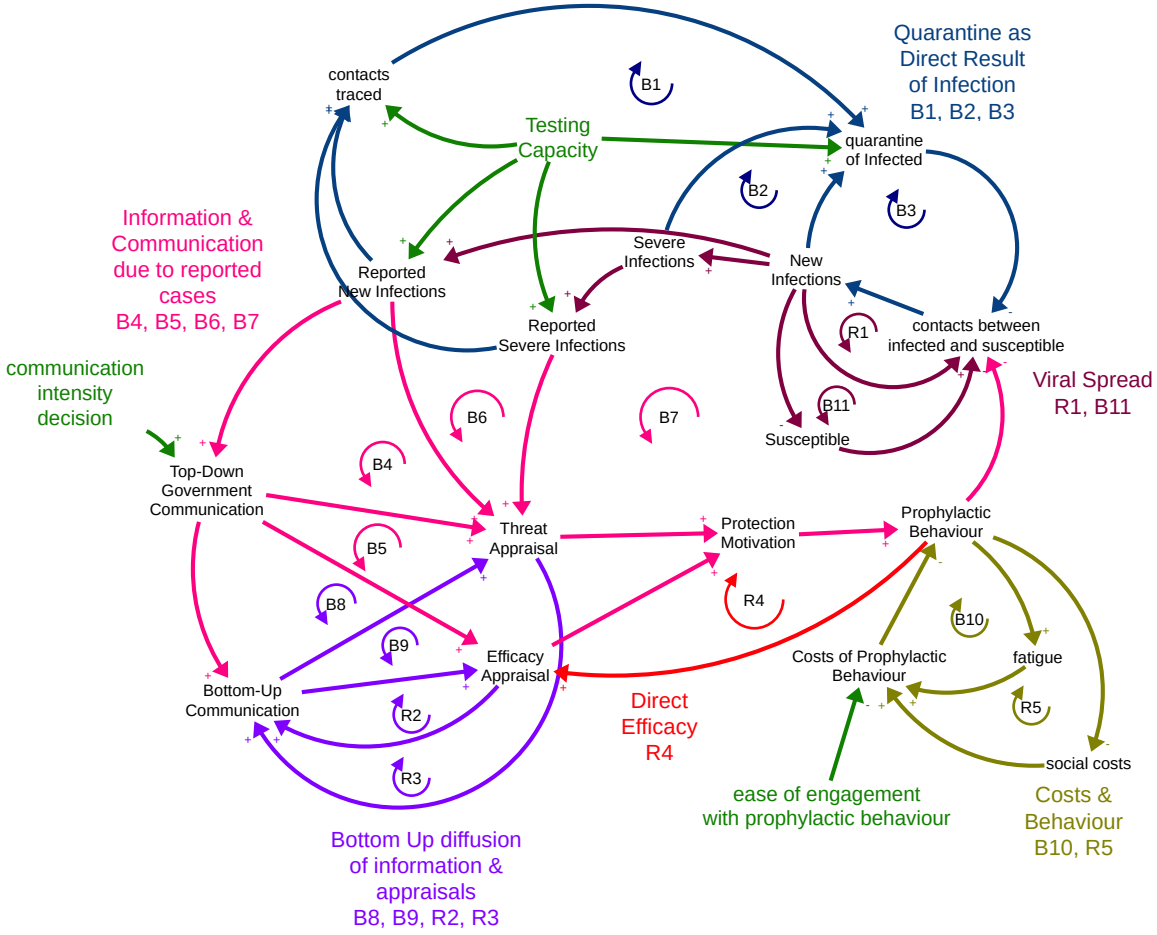


Figure 45: Causal Loop Diagram of the main feedback loops of the full model

As imported cases of Covid-19 enter the country, those Infected people come in contact with Susceptible and Infect them with some probability equal to the infectivity of the virus. New Infections lead to more and more New Infections (R1). The government starts implementing the Testing & Quarantine of infected policies and the balancing loops B2, and B3 start working to slow down New Infections (with B2 being the strongest and, as testing capacity builds, B3 slowly gaining more strength). As the government perceives the New Infections due to testing, they communicate their Threat message activating the response of the population via the balancing loop B4 through the Threat Appraisal. This message is further diffused by the Bottom-Up mechanism (B8) and, together with B5 and B6 which are becoming stronger as Infected people get tested and reported, all loops synergise in increasing the Threat Appraisal and thus the population's Protection Motivation and Prophylactic Behaviour. The Bottom Up mechanism, more slowly, amplifies this effect through the dissemination of the Threat Appraisal (R3) as this is being built through the above-mentioned loops. Parallel to this process, Efficacy-Related information are spread by the government (B5) and the Bottom-Up mechanism (B9 and R3), all acting in the same way as the Threat-Related loops. The balance between those two loop sets is crucial: if the loops passing through Efficacy are not strong enough (B5, B9, and

R2), Protection Motivation will not be as strong and the same applies for the Prophylactic behaviour. Since it is the latter that leads to fewer Infections the next time around, the Reinforcing loop R4 from observations of the response of the population to peoples' Efficacy Appraisal is very significant to ensure that balance between Efficacy and Threat is optimal. The strength of this loop (as well as the main balancing loops through the populations' response, B4 to B9) depend on the Cost mechanisms. The exogenous ease of engagement with prophylactic behaviour is activated first and is the most crucial mechanism: more ease (represented by a reduction in the Livelihood costs for the case of mobility), makes the comparison between Protection Motivation and Costs favourable, leading to increases in Prophylactic Behaviour which, in turn, strengthens the loops that act to slow down infections (B4-B9). Those loops are however counteracted by the Social Costs (R5) that act to maintain the previous levels of prophylactic behaviour: at the early stages those "previous levels" mean no engagement with this type of behaviour. The other type of costs, those due to fatigue (B10) are very weak initially but begin to gain more and more strength over time as the population response loops increase their strength. As B10 becomes stronger, it starts counteracting B4 to B9 loops, as well as the favourable R4 loop[6]. In the meanwhile, B1 gains more and more strength and now all balancing loops passing through New Infections (B1 to B9 since B11 is thankfully very weak) work very well together to slow down the epidemic by weakening R1. This is great news to begin with but a weaker R1 weakens the balancing loops that, now, start working to bring back the system to its previous state: fewer infections lead to lower Protection Motivation, lower Prophylactic Behaviour and hence, more probable contacts between Infected and Susceptible. Simply put, people "relax" and try to return to normality and this might lead R1 to gain momentum once again leading to a second wave (and, not surprisingly, it does). The game is now played in the strength of the balancing loops B1 to B3: if all the time elapsed has been used to build enough testing capacity, those loops will be able to counteract to a large extend the very strong R1 allowing the population response loops to take less load this time around. Of the three, B1 is the optimal as it operates faster and can potentially have the largest balancing capabilities (contact tracing it identifies people at earlier stages thus reducing contacts more quickly). So, how confident are we to put all our bets on B1?

[6] Luckily, B10 and R5 engage in a little «fight» on their own: Fatigue costs increase over time due to the intensity of the Prophylactic behaviour but, at the same time, this intensity decreases the Social costs. The person then, despite being tired from isolation for example, does not see much use in leaving the house when no one else is out

Experimentation with Policies

Scenario No1: Bring back my people

Confidence in testing capacity already in place, worries about the economy, and perhaps even an attitude of "nothing bad happened" lead many governments eager to return to some normality. We will test this option by looking into how the infection rate develops if we return the Costs related to how easy it to practice the prophylactic behaviour (Ease of Engagement in Hygienic behaviour & Livelihood Costs associated with Social Distancing). The assumptions (see Fig 46) represent a return to more usual levels of the variables: for Livelihood Costs, people are needed back to their workplaces, students return to schools, and generally, over time, the consequences of not leaving one's house become the same as they were before Covid-19. For Hygienic Behaviour, restrictions in how many people can, for example, sit together or be in the same bus start disappearing, and disinfectants go back in cupboards (we do assume that the experience has had an impact and that people do not return exactly at the same levels as before Covid-19).

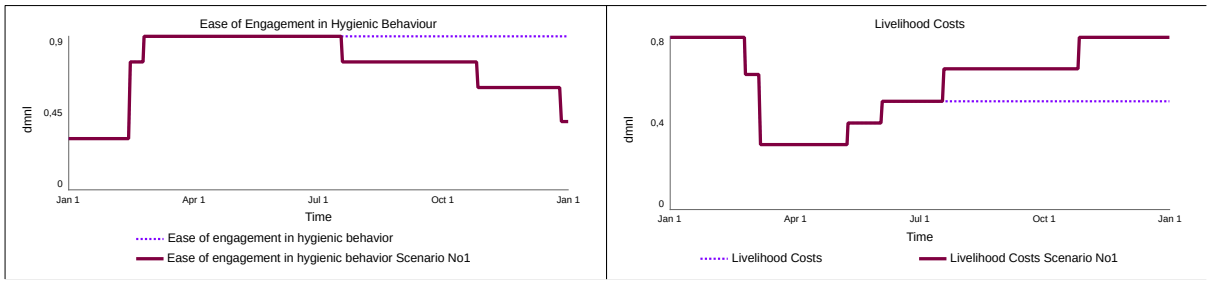


Figure 46: Scenario No1: Ease of Engagement with Hygienic Behaviour & Livelihood Costs. Scenario & Baseline Assumptions

We also strengthen contact tracing to 40 tests performed per positive test and an effectiveness of identification at 20%. To ensure the mechanism works we allow the Testing Capacity to increase with 200 tests/day for the entire year (see figure 47)

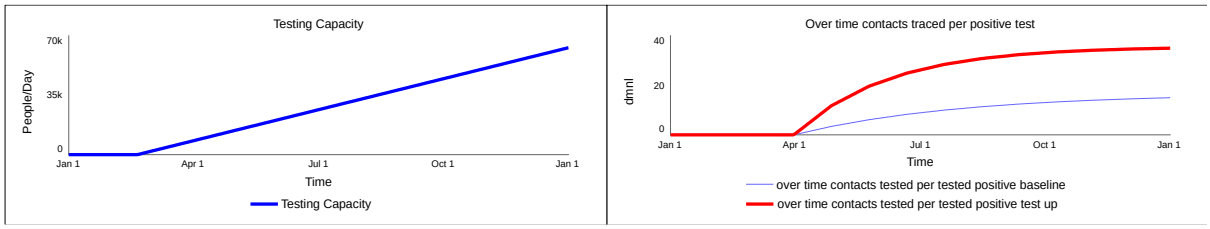


Figure 47: Scenario No1: Testing Capacity and Contacts traced per Positive Test

It is very likely that the 20% effectiveness might not be unrealistically low as it only allows us to identify a maximum of of 20% of the Asymptomatic Infected. We do not know what the actual potential of Contact Tracing might be and which targeted policies can push this effectiveness higher up. However, our results suggest that tracing might not be enough (see Figure 48). Subsequent waves are delayed but,

if the population is faced with costs that do not allow for practicing of Social Isolation and Other Hygienic Measures and thus returns to normal behaviour (as the one we saw at Figure 46), we might be facing very strong waves later on, assuming no vaccine becomes available.

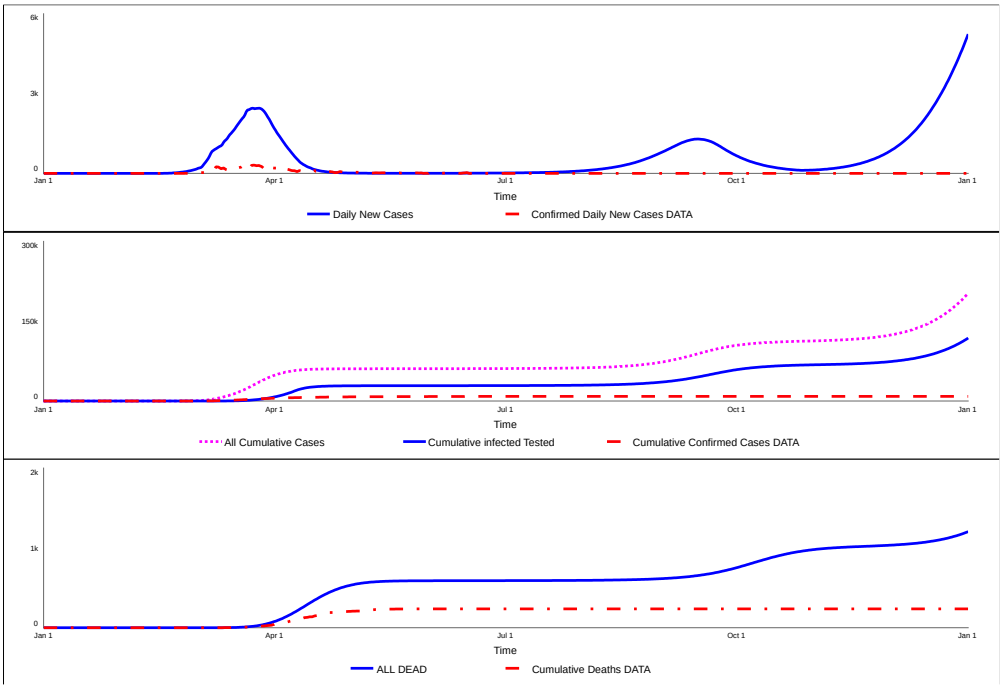


Figure 48: Scenario No1: Results of Daily New Cases, Cumulative Tested, and Cumulative Deaths

It is significant to remember of course that, in our model, we do not quarantine close contacts of confirmed Infected. This additional mechanism might also be strong enough to allow for the reopening policy described here. Moreover, we have not made additional assumptions on how high a fraction of Infected in other categories we can identify (although we can note that the behavioural pattern does not change if we do so).

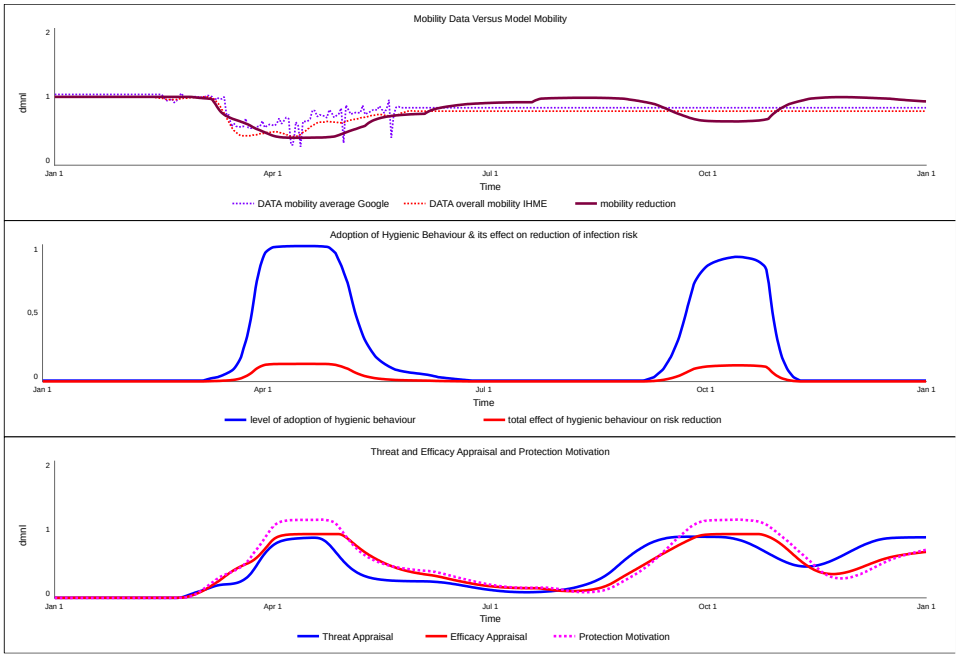


Figure 49: Scenario No1: Mobility, Adoption of Hygienic Behaviour, and Threat & Efficacy Appraisals, and Protection Motivation

What is interesting is that, not only do the actual behaviours return to normal because of the increased costs, but the Protection Motivation seems to suffer as well towards the end of the year (see Fig 49). This is due to the effect of the Efficacy Appraisal and its significance for Protection Motivation. As people do not practice the Prophylactic Behaviours, the effect of observations on one's Efficacy Appraisals make them somewhat "pessimistic" about the efficiency of the proposed response to battle the epidemic this time (others are not practicing it so it will not work). If we had also made the (logical) assumption that the direct Efficacy communication by the government would not be of the same intensity as in the baseline scenario, the picture would be worse.

The purpose of our model is not to make "strong" policy recommendations as we believe that the model's assumptions and the mechanisms that have been excluded might not allow us the most accurate predictions. We do however, feel comfortable to caution, with the evidence we have, against a quick returning to "business-as-usual", until we at least have sufficient evidence of the effectiveness of such policies. Interestingly, we observe what seems the be the "Fear-Control" response (Witte, 1992, 1994): people losing trust in the efficiency of the response and thus stop adopting it. To convince ourselves of the above, we run the simulation a little further: Protection Motivation does never again reach the levels it did before (see Figure 50)

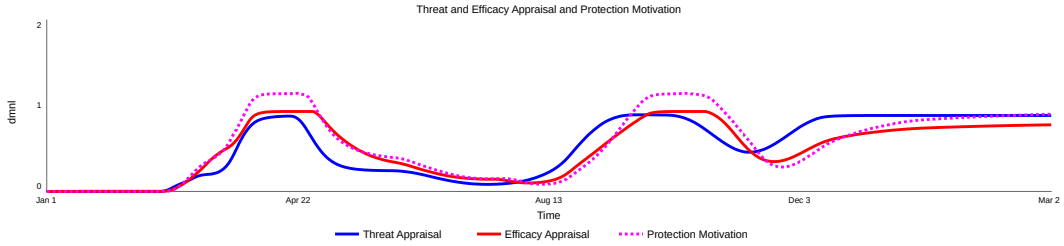


Figure 50: Scenario No1: Threat & Efficacy Appraisal, and Protection Motivation with a longer simulation time

Scenario No2: A little more conversation, a little less action

Utilising only policies that directly target the virus might not be enough. But what about only focusing on communication associated with the behaviour? In this scenario, we will deactivate the contact tracing mechanism in order to see what the effect of communication strategies on the spread of infection might be. We will also *not* manipulate the costs associated with Social Isolation and Other Hygienic Measures (see Figure 46 above for the graph with the baseline assumptions). For this scenario, we will not look at one decision rule but rather at a range of possibilities regarding the intensity of the *Top-Down Efficacy-Related communication message* by allowing the parameter *intensity of Efficacy Related communication* to take values between 1 and 2. As a reminder, the Efficacy-Related communication message by the government is controlled by the effect of new reported cases on the government's communication message: the government is thought to perceive the risk posed by Covid-19 and respond with a Threat-related and an Efficacy-related communication message with an intensity controlled by the intensity of Threat-and intensity of Efficacy-Related communication message which are, at baseline, at the values of 1 and 1,15 respectively.

As can be seen in Figure 51, stronger Efficacy-Related messages do have an impact as they lead to fewer infections, however communication tactics are *not* sufficient without targeted testing of contacts (results of the baseline scenario with an intensity of Efficacy-Related communication equal to 1,15 and contact tracing ON are shown in the pink, thicker line). Besides a larger second wave, the infections do not "die out", or oscillate as we have seen before but approximate an equilibrium that is dependant largely on a new model-produced "normality" of reduced mobility and high adoption of hygienic behaviour (see Figure 52) .

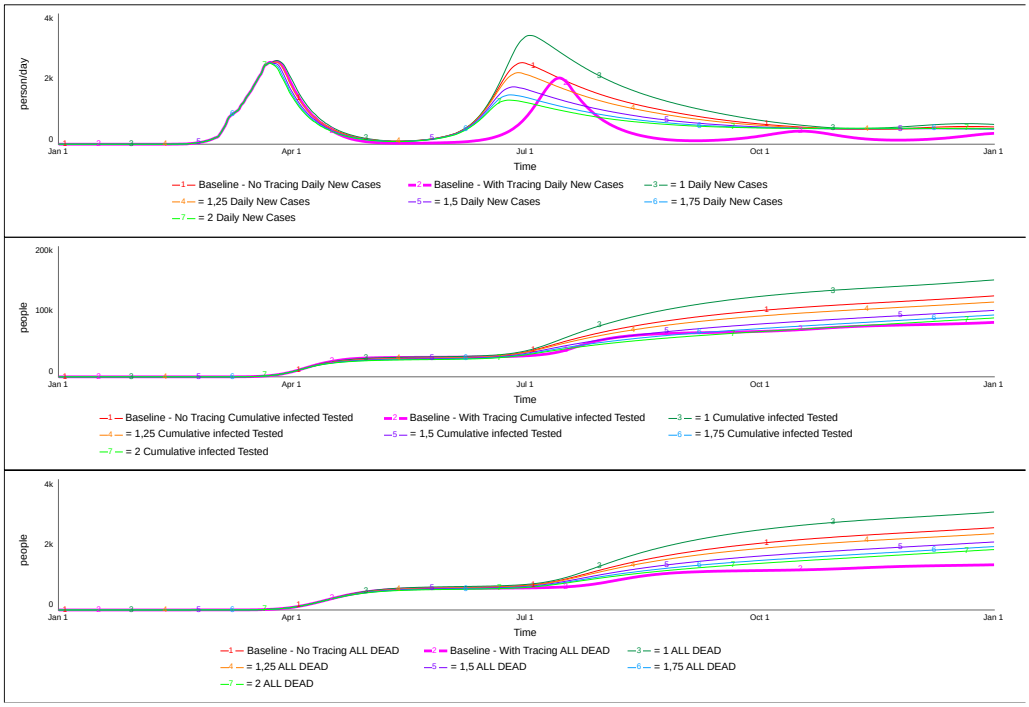


Figure 51: Scenario No2: Daily New Cases, Cumulative Infected Tested & Cumulative Deaths for various values of intensity of Top-Down Efficacy-Related communication message

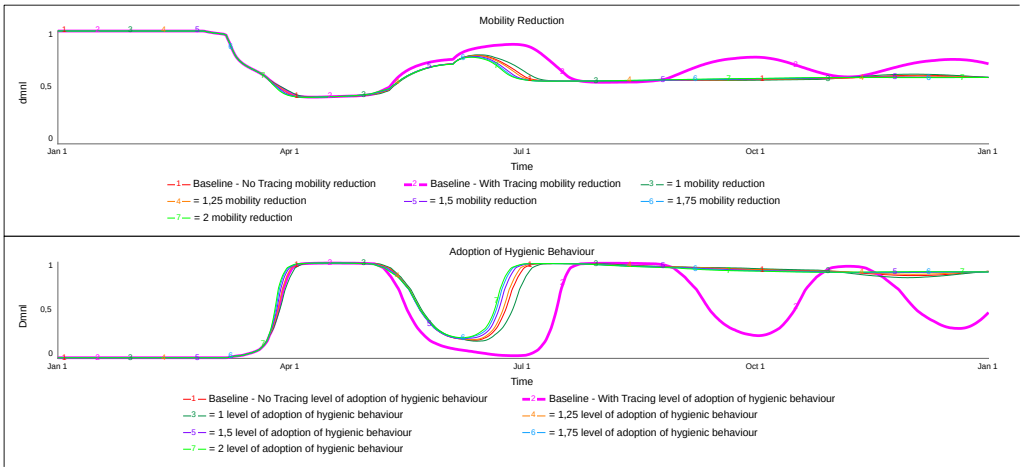


Figure 52: Scenario No2: Mobility Reduction and Adoption of Hygienic Behaviour for various values of intensity of Top-Down Efficacy-Related communication message

The effect of Efficacy communication is not in the absolute Efficacy Appraisal of the population but mainly on the speed of increase (Figure 53). An emphasis, by the government, on the efficiency of the Social Isolation and Hygienic response, or perhaps an even more general focus on messages that emphasize that there are ways to mitigate the Threat is exhibited here, in line with the descriptions of Protection Motivation Theory (Rogers, 1975) and the Extended Parallel Process Model (Witte, 1992).

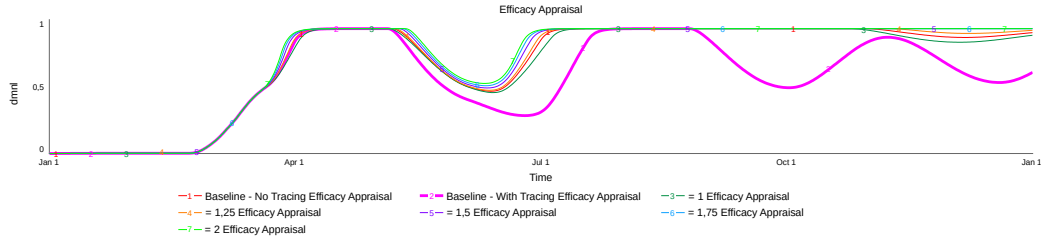


Figure 53: Scenario 2: Efficacy Appraisal for various values of intensity of Top-Down Efficacy-Related communication message

But what about Threat-Related messages? Witte & Allen (2000), among others, have proposed that best results are observed under strong Threat-Related and strong Efficacy-Related messages. We test values between 1 and 2 (normal and double intensity) for each of the messages and the results are presented in Figure 54. Again, the absence of the contact tracing mechanism leads to a worse picture no matter the communication intensity. However, manipulation of the content of the messages does lead to differences in the overall behaviour with the worse policies combining strong Threat messages with low Efficacy messages (Run 5, in light blue gives the most unfavourable development with intensities of Efficacy message = 1, and Threat message =2)

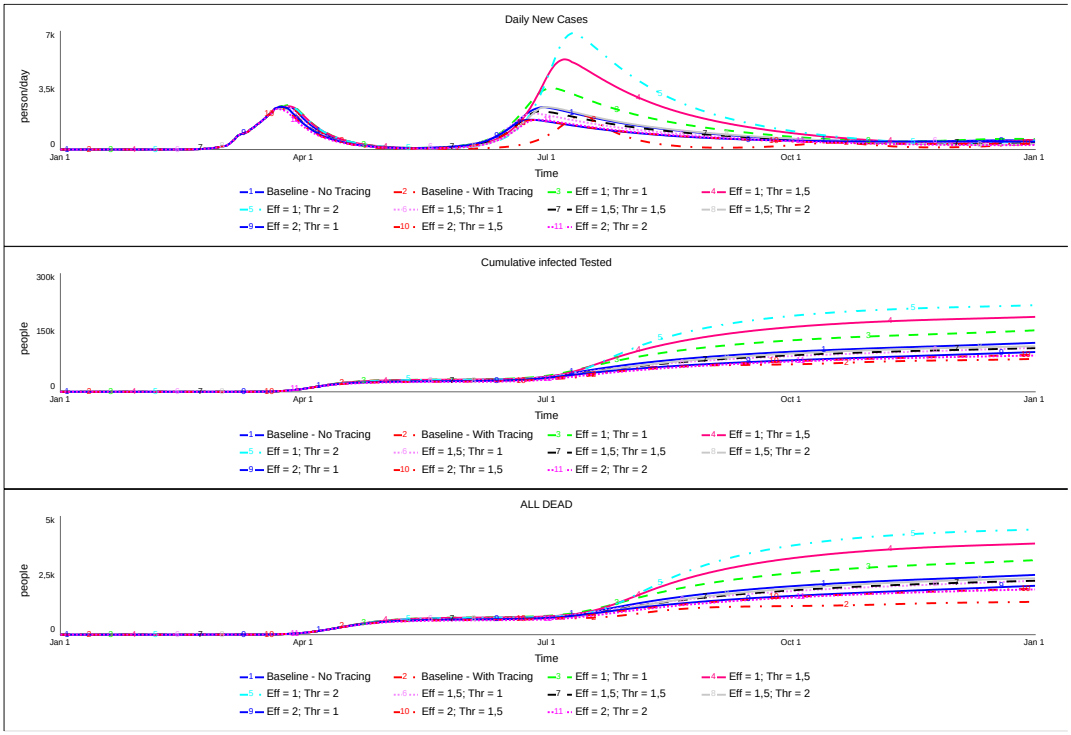


Figure 54: Scenario 2: New Cases, Cumulative Tested and Death for various values of Top-Down Efficacy and Threat Related communication message

Not surprisingly, the best results, coming somewhat close to the Baseline-with Tracing policy are observed under strong Threat and Efficacy messages combined, with the magnitude of the Efficacy message making most of the difference (Runs 9,10, and 11 when Efficacy is communicated with double

the normal intensity). Is there any however that high Efficacy messages can "backfire"? There is a possibility that we can imagine through the *costs of fatigue*. Communication messages that are very efficient in eliciting the response of the population, could lead to more fatigue of the population that eventually counteracts this response (the small B10 loop from Fig. 40). Strengthening the loop by reducing the time to update perception of recent distancing intensity and of recent hygienic behaviour intensity to 1/3 of its original value (hence, to 10 days), slightly changes the picture. Higher intensity of Threat and Efficacy still give the optimal results, but, in this case, the difference with more moderate values is disappearing. Moreover, due to the effect of fatigue, the difference in effectiveness between the Tracing Policy and the Communication optimal policy is much lower (see Run 2 and Run 11). This is an interesting behaviour that should be further explored as, if it does represent the real system, it might indicate that "rationing" or "saving" some communication for later could be beneficial. While this might be not very much the case for an infectious disease, it could be more relevant to other, "slower" threats.

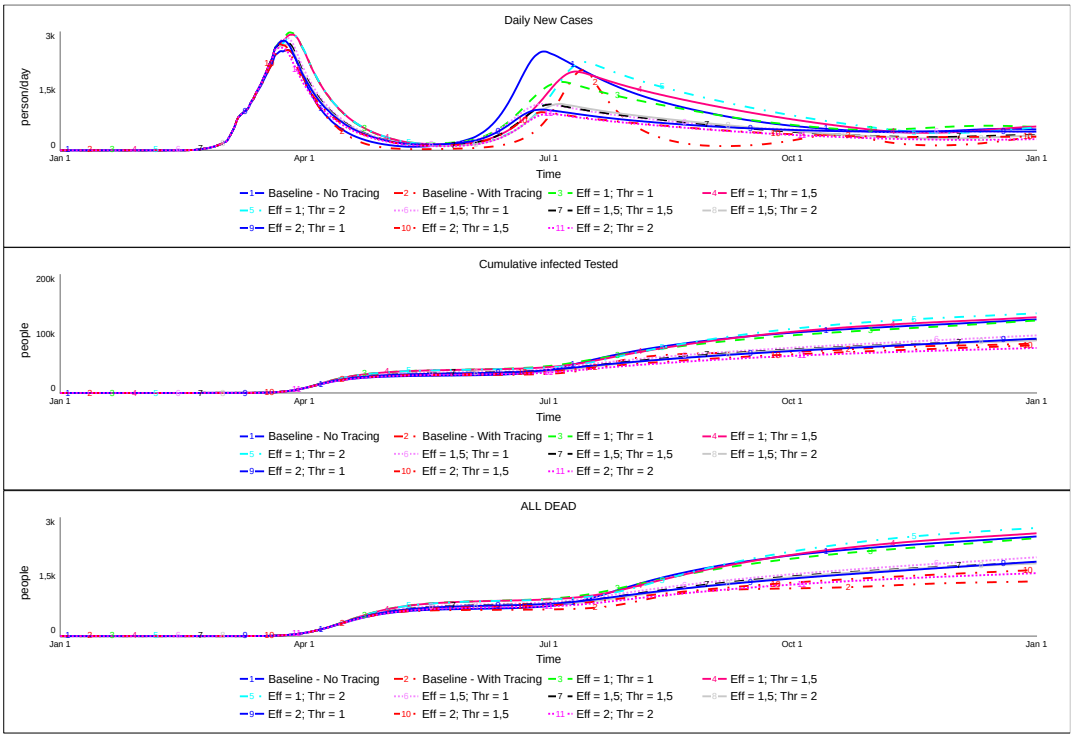


Figure 55: Scenario 2: New Cases, Cumulative Tested and Death for various values of Top-Down Efficacy and Threat Related communication message with faster Fatigue

The above results are, as expected, in line with the theoretical and empirical assumptions that were built into the model. While we believe those to be reasonable and in line with current understanding of the Threat-Efficacy relationship, COVID-19-specific evidence can greatly benefit the validity of our results.

So, what about you and me?

To conclude the experimentation with communication messages, we should make one final test to examine whether the Bottom-Up communication choices can have any impact in COVID-19. We will here only manipulate the Intensity of the Efficacy-Related communication message and do so only for the Bottom-Up mechanism. This intensity is a "multiplier" of our own Efficacy beliefs; a choice representing how much we amplify in our message our own perception of how effective a response might be. We will again test with values between 1 and 2 (normal and double intensity). Figure 56 suggests that such a decision might indeed make some difference, even in the presence of stronger policies such as the contact tracing one. The only effect we manipulate here is that of the communication message; all other behavioural choices that might influence perceptions and costs associated with the behaviour are not manipulated although they are very well expected to have additional favourable impacts.

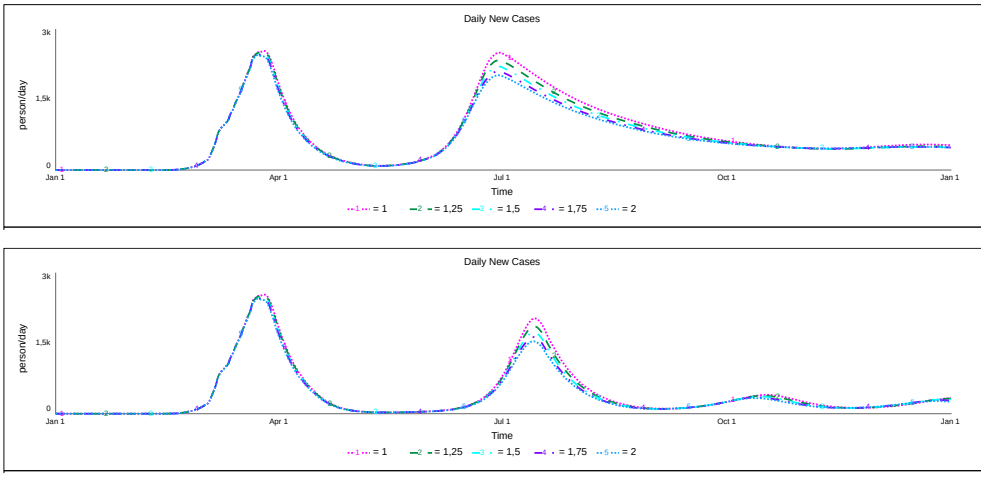


Figure 56: Scenario No2: Daily new cases for values of the Bottom-Up Efficacy-Related communication message with no contact tracing (top) and with contact tracing (bottom)

"Scenario" No3: Experimentation with Communication messages

In this "scenario", we will try to look closer in some sensitive values and what can we potentially derive from them. We will run some experiments and present their results and whether those can tell us anything about communication decisions under uncertainty of parameters.

Is Proactive Communication beneficial?

The decision rule, by the government, on when to start communicating Threat and Efficacy messages related to COVID-19 has been endogenised in our model with the use of an *Additional Top-Down Threat* and *Additional Top-Down Efficacy Communication* mechanisms. This mechanism is more sensitive to first observed cases of COVID-19, leading the government to start sharing communication earlier, and the results of the activation and deactivation of the mechanism can be seen in Figure 57.

While the mechanism is not perfect, it does lead to an earlier communication spike and that is sufficient for our exploration.

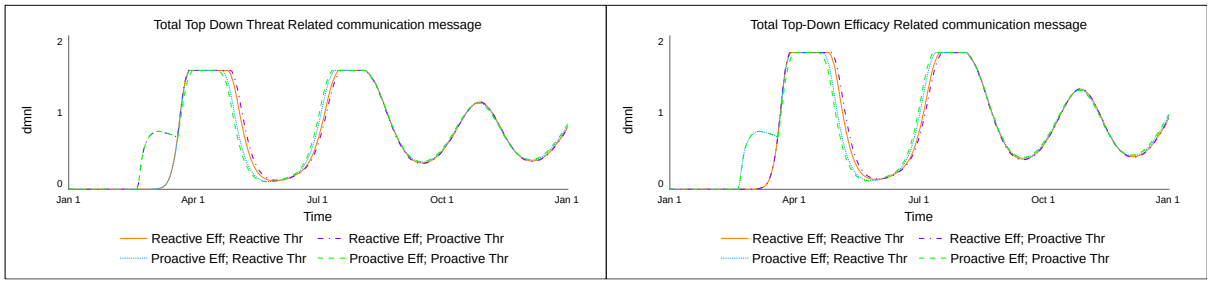


Figure 57: Threat & Efficacy-Related Top-Down communication messages with Proactive and Reactive decisions

We do observe that proactive communication has a significant impact on the first wave of infection with optimal results obtained when both messages are emphasised early on (Proactive Eff; Proactive Threat). We also see that Proactive Threat messages that are not accompanied by Efficacy messages (Reactive Eff; Proactive Threat) are not advised under our assumptions regarding the "Fear-Control" response: early Threat-focused messages without information about whether the proposed behavioural response "works", are not expected to lead people to follow the responses, thus increasing the observed number of infections.

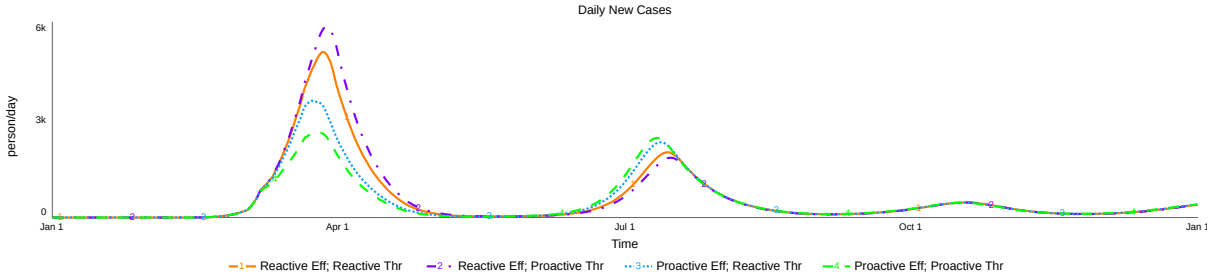
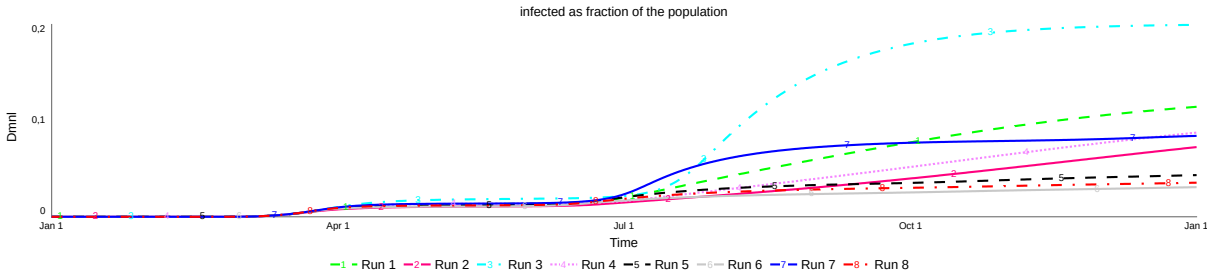


Figure 58: Development of Daily New Infections under with Proactive and Reactive decisions of Top-Down Threat and Efficacy-Related communication messages

It is important to note that, in the second wave, the proactive mechanism is not active, and the faster spikes are the result of the better management of the first wave. A faster declining first wave leads people to return towards their baseline mobility faster, thus bringing forth a speedier second wave.

What if Threat Appraisal is more Important?

In this test, we will look at the relative contribution of Threat Appraisal on Protection Motivation. The Baseline value we have used is 60% but it is possible that Threat has a higher effect. We look at the overall fraction of population that becomes infected with COVID-19 in order to view the results of this experimentation in a more easily visible way. What we observe is that, even if Threat is more important for peoples' Protection Motivation, higher and faster Efficacy messages still have a positive influence (Run 8 in Fig. 59)



Run	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
relative contribution of Threat Appraisal on Protection Motivation	0,3	0,3	0,3	0,3	0,8	0,8	0,8	**0,8**
Delay in Efficacy communication relative to Threat communication	0,5	0,5	7	7	0,5	0,5	7	**7**
intensity of Efficacy Related communication	1	2	1	2	1	2	1	**2**

Figure 59: Testing with different contribution of Threat on Protection Motivation, and intensity and delay of Efficacy Communication

What if building one's Efficacy Appraisal is a slower process?

It is plausible that people react faster to Threat-Related information than to Efficacy-Related information due to risk aversion or even trust in governmental or scientific suggestions. What if this is true? In our baseline scenario, we have assumed that both Threat and Efficacy Appraisals update rather fast (3 days delay). We will look here at a scenario where Efficacy updates three times slower than Threat does (so, with a 9-days delay). For brevity, we will present here the development of the fraction of the population that is infected and will focus on what strategies we could use if Efficacy is indeed a slower process.

The first strategy is to decrease the delay by which we present Efficacy-Related information relative to Threat-Related information. The more delayed the information, as expected, the worse the results (Fig. 60)

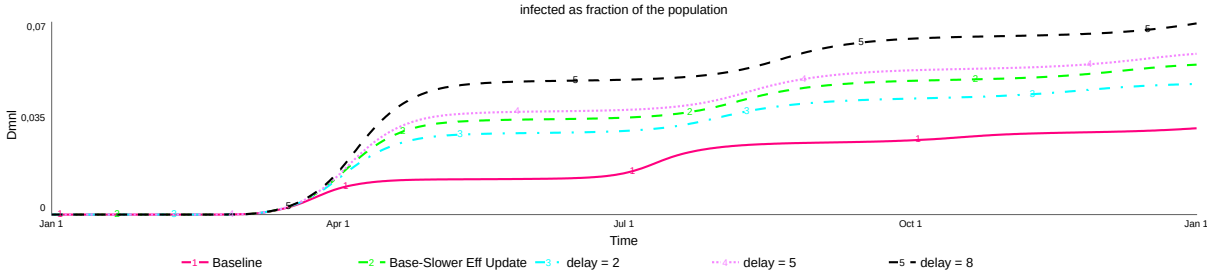


Figure 60: Testing the prevalence of the virus under different values of delay in the communication of Efficacy

Does this still hold if the effect of Efficacy on Protection Motivation is lower? We experiment here with the weight of Threat Appraisal on Protection Motivation: higher values of the weight denote a higher

significance of Threat Appraisal for peoples' intention to act against the Threat. Higher delays in Efficacy communication are not beneficial, even if the Threat is much more significant for people's motivation (see Run 8 in Fig. 61 with an 8-days delay and a contribution of Threat on Protection Motivation accounting for 80%).

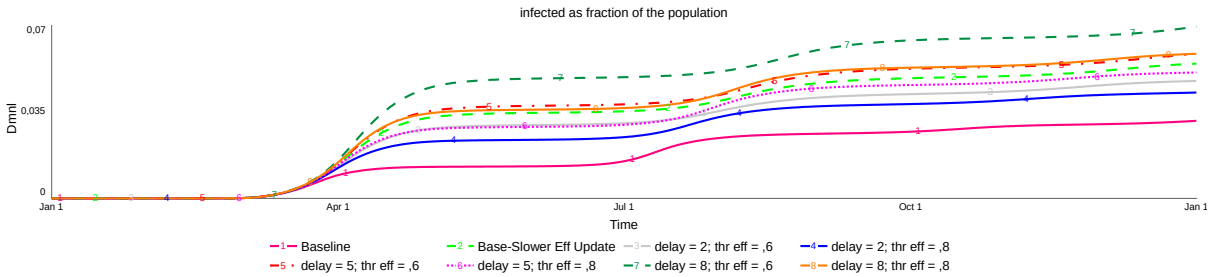
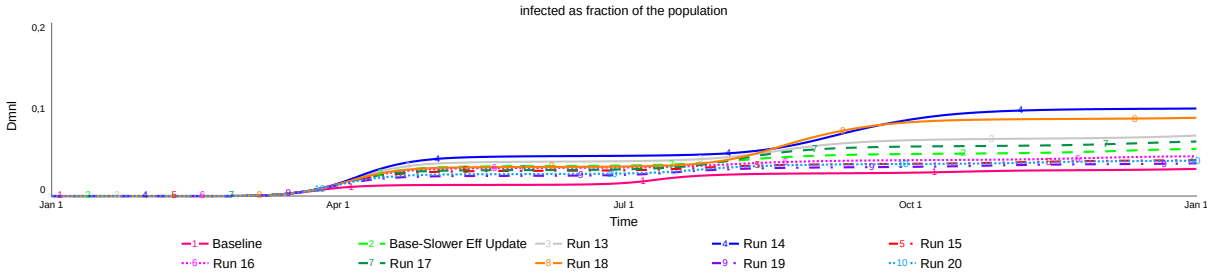


Figure 61: Testing the prevalence of the virus for slower updating of Efficacy Appraisal

Let's perform a final test: if indeed Efficacy is not as significant for intention, can we then just increase the Threat message and get similar results? Well, this might be risky: we can see a **not** optimal development even with a high contribution of Threat on Protection Motivation *and* a high Threat-Related messages (Run 8 in Figure 62). Similar results are observed if Efficacy updates equally fast as the Threat, but if the former is indeed slower, those effects are amplified.



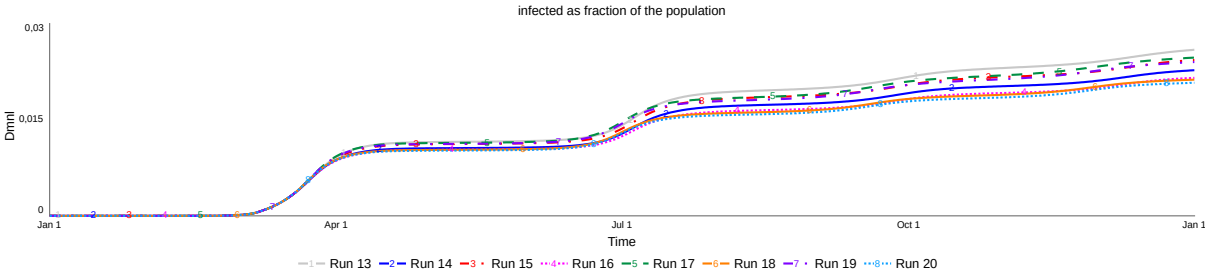
Run	13	14	15	16	17	18	19	20
relative contribution of Threat Appraisal on Protection Motivation	0,6	0,6	0,6	0,6	0,8	**0,8**	0,8	0,8
intensity of Efficacy Related communication	1	1	1,5	1,5	1	**1**	1,5	1,5
intensity of Threat Related communication	1	1,5	1	1,5	1	**1,5**	1	1,5

Figure 62: Testing the prevalence of the virus for slower updating of Efficacy Appraisal and different Threat communication intensity

To summarise, if we consider that the relationship between Efficacy and Threat indeed plays a role in making people engage in "Fear Control" reponses (that is, deny or discount the threat due to the lack of sufficient ways to mitigate it), we need to be mindful of how fast perceptions update.

So, what if there is no such thing as Fear Control?

All our analyses so far were assuming the Fear Control zone. What if they got it wrong and this response is not there? The optimal results are still indisputable: high Threat *and* high Efficacy messages still produce the best results



Run	13	14	15	16	17	18	19	20
relative contribution of Threat Appraisal on Protection Motivation	0,6	0,6	0,6	0,6	0,8	0,8	0,8	**0,8**
intensity of Efficacy Related communication	1	1	1,5	1,5	1	1	1,5	**1,5**
intensity of Threat Related communication	1	1,5	1	1,5	1	1,5	1	**1,5**

Figure 63: Prevalence of the virus with manipulations of Threat and Efficacy communication intensity in the absence of "Fear Control" mechanism

This short experimentation has made clear that strong Efficacy messages are beneficial under all circumstances, even more so when they are coupled with strong Threat messages. This is supported by the literature, however, we need to be very careful with such an assertion: if there is any evidence that the relationship between Threat and Efficacy is different at different regions (or ranges) of these values, then there might be a chance that strong Efficacy messages do not work in the way we have seen here and might instead impede our ability to combat the environmental threat. The questions becomes: is there any region of Threat where, if we believe in the Efficacy of the response, we might discount the Threat instead of be motivated to act against it? This experimentation opens up an interesting direction for further iterations of the model.

Chapter 5: Discussion

> [S]ince behaviour is the central issue, we must be careful about how we model it and strive to incorporate behavioural considerations more fully into our analysis of disease control. We cannot simply rely on traditional analyses that do not model behaviour but augment these with ad-hoc interventions that rely on guesses about compliance rates. The standard epidemiological models are an excellent starting point for analysis but must be made complete by fully integrating them with more sophisticated models of human decision-making and behaviour."
>
> (Toxvaerd, 2020, p. 2)

Overview

This thesis has attempted to contribute to the understanding of the COVID-19 crisis through a simulation model that focuses on the coupling of the dynamics of infection and those of the behavioural response of the population. We have used Norway as a case study to test the validity of the proposed structure. Mainly, this work has been a first attempt to combine and translate Health Behaviour theories in a formal System Dynamics simulation model and our main emphasis has been on the communication messages that governments can utilise to mobilise the population. To our knowledge, this is the first modeling study that focuses on communication messages, at least for the case of COVID-19, and we hope it can assist in the conversation around how to elicit an adaptive response of the population.

To summarise, our goals for this thesis were:

I. Main Infection Model: Modification of classic SEIR model to:
   a. Account for a gradual progression across severity stages of a disease & one that breaks "perfect-mixing" rules.
   b. Offer a more "individual-level" view through following an infected persons' journey over the infection duration and at different severity stages
   c. Allow for association of different characteristics according to the day of infection and severity stage (e.g. viral load, relative infectivity, etc.)

II. Behavioural Structure: Develop a model that can provide:
   a. Endogenous view of behavioural response of the population to COVID-19, and one that is not only anchored only on virus prevalence or mortality.
   b. An attempt to represent psychological theories of response to environmental threat to one's wellbeing in a formal, computational model that can be tested
   c. A structure that allows testing of policies targeting *directly* peoples' response instead of only policies that focus on management of the virus. Such policies are related to

i. The drivers and the communication of Threat & Efficacy, as well as Proactive vs Reactive communication strategies
ii. The costs that might influence peoples' decision to comply with the proposed measures

Limitations & Further Directions

J. W. Forrester said: "The beginner is more conspicuously vulnerable to including too much than he will be after some experience in building models and after the discovery of how much simplification is possible" (1961, p. 453). Not surprisingly, we have experienced this vulnerability rather heavily in the development of this work. Further iterations could benefit from some simplifications, however, an assessment of the communicability of the model is very significant to inform further steps

Main Infection Model

As we have mentioned, there are many limitations regarding our current knowledge of the virus and, as such, the model needs to be updated as new evidence emerge. Importantly, our representation of the testing mechanisms is underdeveloped and while this was not the main purpose of our model, future iterations can benefit greatly from better representations of testing mechanisms, especially regarding the possible effectiveness of contact tracing. Moreover, our model is a high-aggregation one, looking at the entire population without consideration of geographic information and age cohorts. Networks dynamics are significant for the spread of an infectious disease (see, for example Isham et al., 2011; M. J. Keeling & Eames, 2005) and, as such, our model could greatly benefit from those. Despite those limitations, it is a priority to apply the structure to other countries, especially more data-rich, to further assess its validity.

An interesting area in which to expand would be the effectiveness of contact tracing. Its effectiveness has been emphasised and proven, and there is an area that fits very well with our explorations of the population's responses; that of the adoption of contact-tracing apps. In Norway, the application "Smittestop" from the Norwegian Institute of public health had, as per May 19, 641824 active users and a total of 1554620 downloads (Norwegian Institute of Public Health, 2020). These apps can be effective as long as a sufficient number of people adopt them. Adopting such an app might rely on Threat-Related perceptions (as well as app-specific Efficacy appraisals) but might also feed back to them: the might lead to a sense of "false safety" – a perceived reduction of the risk of the virus that can have opposite to the desired effects. There is a possibility that tipping points exist and a model exploring those while also taking into consideration decision making at the individual level could assist in the strategy going forward.

Behavioural Model

The behavioural model has many limitations. There is of course a very high uncertainty of parameters and non-linear relationships, and evidence of evaluations of the population's perceptions can greatly enhance its ability to discuss the response of the population to COVID-19. Very importantly, the main assumptions regarding the relationship between Threat and Efficacy need to be further evaluated: if there is any evidence that the relationship is not in the same direction or intensity at different regions, the main assumptions need to be adjusted accordingly, as they might produce results opposite to those we have seen here. The drivers of Efficacy need also additional support and evaluation. We hope that the very intensive research efforts focusing on the response of the population to COVID-19 can provide us with further data of peoples' perceptions at different stages of the pandemic that can assist us in clarifying the described mechanisms. Very importantly, evaluations of the effect of different costs on peoples' decisions, especially those related to fatigue, are very crucial and we might have presented a much more optimistic picture than the real one. Besides better clarifying the relationships between variables, we believe that further iterations can benefit from translating some of the variables to accumulative mechanisms as well as further explicit diffusion processes in the population ("trends" & social costs, Efficacy-Related information, etc). These will be a better representation of reality and will increase the applicability of the theory / model to other Threats. As with the main infection model, applying the model to other case studies is a good way forward.

If additional support can convince us that the model's assumptions are valid and the structure has been updated accordingly, then we should definitely look more closely into the spread of misinformation, as well as further diffusion processes between the population. The element of trust in the government and the information provided by the government is expected to have a very significant contribution (Khosravi, 2020; Siegrist & Zingg, 2014). For the Norwegian population, trust was reported to be rather high, however, there have been evidence that it increased during the COVID-19 crisis . Trust might alter the relative contribution of messages disseminated by the Top-Down and by the Bottom-Up mechanisms (we don't trust the government so we turn to other ways of receiving information) which might produce interesting dynamics and, combined with spread of misinformation or other non-beneficial person-to-person communications, can have a very significant impact on the observed behaviour.

Research Questions

Can well-known models of infectious disease be adopted for the case of COVID-19?

Yes. The model of gradual progression that was proposed by Pål I. Davidsen and developed as part of this thesis does replicate rather well the reference model of behaviour. While there is need to apply the model in other case studies, as well as compare it with the standard SEIR model or other known

modifications of it, we are confident that the behaviour it produces is within reasonable ranges. Updates with more recent information regarding the virus are of course crucial, not only for this model but all COVID-19 simulation models.

Could accounting for gradual progression among stages of the disease accurately describe the reality of Covid-19?

It does seem so, yes. The growth patterns of the more severe stages are represented quite well through our model. There are of course limitations due to lack of knowledge of the growth patterns of less severe infections, however the overall rational behaviour makes as optimistic as to the realism of this structure. Again, further validation can make us answer more confidently.

Can such a model offer us additional information?

Yes. Being able to see individuals' progression across stages of their infection and days since infection is a very good addition to standard epidemiological models. It makes the association of characteristics easier and allows us somewhat of "individual-view" of the journey of an infected person. Tracking individuals, we believe, can also increase communicability of the model's results. We would find a very interesting addition the association of common symptoms or experiences that can easily be tracked based on the structure

Could such a model be utilised for other viruses or diseases?

Yes. Gradual progression is more common than not. It would be interesting to apply this model to diseases with longer duration and track individuals' symptomatology over time. The clearer separation of various stages of the infection duration can perhaps provide valuable information on necessary health care capacities, medication, or other resources in cases of epidemics with long-term effects.

Is the behavioural response of the population, in terms of compliance with proposed behavioural measures, significant for the prevalence of Covid-19 in the population?

Most certainly yes. This is of course already a known fact both to the scientific community and, due to the recent experiences, to policy makers[7] and the general public. There might however not be a similar level of agreement on whether it is **still** significant. With more and more capacity put in place and perhaps an acquired optimism after the first wave, there is an eagerness to return to life-as-usual. We need to be very cautious with such an approach. Despite significant limitations in our assumptions regarding the testing policies and capacities, our model suggests that should avoid "putting all our eggs in one basket". As countries start reopening, we need to be careful with making the practical costs of prophylactic behaviour as high as they were before COVID-19. Motivation to protect ourselves against

[7] Well... Rather, "to *most* policy makers".

the virus *does* decline over time and as infections remain low, and since our engagement with prophylactic behaviours depends on a balance between motivation and costs, we need to at least keep the latter at manageable levels to be able to maintain some degree of mobility reduction and other hygienic measures that can help us avoid new waves. We have already built some institutional capacity that reduces the cost of a person's decision to "stay at home today" and it seems a very good strategy to maintain it, at least for the fraction of population that we can.

If so, is it sufficient that this response is grounded in the prevalence of the disease?

It depends on the purpose of the model. If one wants to test policies targeting the virus directly (e.g. contact tracing), then grounding the population's response on the prevalence might be sufficient. However, one must be very careful: Threat-Related perceptions fade over time and fatigue of the population practicing the response or even talking about it are very important. If we do not account for them, prevalence-elastic response assumptions can make us underestimate significantly the necessary intensity of policies targeting the virus. More importantly, we have seen first-hand in the case of COVID-19 how capacity constraints and delays in the development or increase of, for example, testing equipment can really slow down our efforts to directly address the virus. In such cases, the population's response becomes our main weapon, and prevalence-elastic response approaches do not allow much space for understanding and testing poliies on how to best mobilise it.

Incorporating the element of Efficacy, in particular can be very valuable. We perceive the efficacy contribution to extend beyond health-related behavioural intentions in times of crisis to other responses to Threats as, for example, related to sustainable usage of resources (Lam, 2006) or climate change action (Doherty & Webler, 2016). Especially for the latter, there has been research suggesting that strong threat focused messages do not work and might even have counteracting effects (O'Neill, Boykoff, Niemeyer, & Day, 2013; Wibeck, 2014). Efficacy might very well be a missing link that can allow us to understand how to best communicate information about the significant Threats we are collectively facing.

Are there additional mechanisms that can be utilised to enhance compliance with proposed behavioural measures? More specifically, are communication messages important in helping generate the desired response?

Absolutely. Communication messages are very important in building Protection Motivation against the virus. This Motivation is a significant predecessor to action and needs to be built and sustained to improve the management of the virus. We have already seen that communication and information campaigns have proven on many occasions a very valuable tool for the control of COVID-19 in reality, and our model supports this observation. The decisions we make, at the top level, on *when* to start communicating and *how much* to communicate are very important. The absence of clear, efficient, top-down information has a strong impact on the population's response as it slows down and reduces their

perceptions of the environmental Threat as well as the Efficacy of the response. Additionally, it could potentially leave space to the spread of misinformation which, while not present in our model, would act to slow down the development of the assessments leading up to Motivation to act.

It is also important to note that communication messages directly between people are also valuable. What we share matters. We have indeed observed in reality an enormous response, especially by the scientific community, to spread information directly, via social and traditional media, both regarding the Threat of COVID-19 and the Efficacy of the response. Our model supports that this indeed works, even with significant limitations in quantifying "how much" it works. It is, we believe, important to remember this and not underestimate the contribution of our own communication messages.

Can targeted information regarding the effectiveness of the proposed measures have a significant impact?

Yes. There is both theoretical and observational support that the Efficacy of a behaviour is very significant for us practicing the response (for a review see Maloney, Lapinski, & Witte, 2011). The model was able to showcase insights from behavioural theory stating that communication of Threat, if not accompanied by communication of the Efficacy of the response can lead to "fear control" strategies such as defensive avoidance of the threat, rather than adoption of the proposed measures. There is need for more research on this mechanism, as well as further exploration of the main drivers of both Appraisals and the delays in their increase, however, the point holds even if the effects of Efficacy are not very strong, they still can have an impact on our behaviour.

It is therefore advised to communicate messages focusing on solutions and emphasizing the effectiveness of responses to a threat in order to mobilise people to act. This, as well, applies not only for centrally distributed messages but for our individual communication as well. Emphasizing Efficacy-Related messages, whether those contain practical information and scientific facts, or more "emotional" content can help. If images of successfully baking sourdough bread and making the perfect Dalgona coffee[8] get the message across that "we can fight the pandemic" because we are collectively practicing an efficient response to it, then we should absolutely utilise them.

Can existing theoretical frameworks of decision making in response to environmental threats to our wellbeing be combined in a unified framework?

This has been our attempt. Our review of main Health Behaviour Theories, as well as relevant computational models, has convinced us that there is more that is common than different. We strongly believe that combining theoretical frameworks is important for scientific production and for policy recommendations. Regarding the former, we see science as benefiting from both convergent and divergent knowledge activities, but it is our belief that, at this point in time and after a long history of

[8] Just a few of the "food trends" of the pandemic (Liaw, 2020)

divergence, we need to converge to remain relevant. Bringing established knowledge together is happening but *more* is needed if our goal is to assist with the big problems of our time. Policy makers are in need of clear, combined frameworks that can help them understand and better utilise decision-making processes of the population, and the need for convergence is more significant than ever. We see computational approaches are the most suitable to facilitate convergence in science and, perhaps most specifically, in social and psychological science.

In our own model, we have attempted and, to a hopefully reasonable degree, managed to bring together elements of most of the main Health Behaviour Theories in a unified framework that is reasonable. Our work has led us to believe that there is *not* much more that needs to be incorporated, although there is a need for better representation of the mechanisms (either by better quantification of relationships or by utilizing more diffusion components or representing some mechanisms of perception updating or change in general as accumulations). Additional experimentation is necessary but a such a framework for response to threats can be very valuable.

Can they be translated and represented in a dynamic, computational model and, if so is System Dynamics an appropriate method?

Absolutely. This is of course no news, but we hope our initial exploration further supports this fact. Simulations can be an extremely useful tool to translate theoretical constructs, incorporate evidence that have been acquired through studies of established theories, and experiment in a safe space. Experimentation via simulation can provide validation of or help further develop such constructs and, equally or even more so importantly, can assist in communicating their insights in a way that might be more engaging both for policy makers and the general public.

We see many opportunities for psychological insights in their translation in System Dynamics models and even more so in the ways they can be used as artifacts to help facilitate change. Theoretical knowledge can and should be represented in such models, despite the challenges in quantification. This work has been a first attempt in this representation and there is much more to be done for the specific area of threat management and processes of behavioural change.

Is such a framework relevant only for the COVID-19 pandemic?

No. Looking at public response to an environmental threat utilising behavioural theories (and with explicit inclusion of message communication components) has possible applications beyond the management of COVID-19 and other threats directly related to Public Health. Protection Motivation Theory for example, offers support for this statement as the framework has been utilised to explore, among others, adoption of sustainable agricultural behaviours (Keshavarz & Karami, 2016) particularly as related to climate change (Luu et al., 2019), organizational threats for Cyber Security (Bauer & Bernroider, 2015; Herath & Rao, 2009), as well as general change in mental models through methods such as Group Model Building (Rouwette, Korzilius, Vennix, & Jacobsa, 2011). Processes of change

and our responses to the environment and the threats around us are very significant. We hope that this first iteration of combining behavioural insights and describing them in a System Dynamics can continue improving, and that it manages to assist our understanding of how to bring about positive change.

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Appendices

Appendix I: BaseRun Parameters

Parameter	Value
ADDITIONAL TOP DOWN THREAT COMMUNICATION SWITCH	1 (ON)
ADDITIONAL TOP DOWN EFFICACY COMMUNICATION SWITCH	1 (ON)
intensity of Efficacy Related communication	1,15
intensity of Efficacy Related communication Bottom Up	1
intensity of Threat Related communication	1
Delay in Efficacy communication relative to Threat communication	4 days
Livelihood Costs	As in Fig. 25
Ease of engagement in hygienic behaviour	As in Fig. 25
time to update Efficacy Appraisal = time to update Threat Appraisal	3 days
time to discount a severe case	7 days
relative contribution of Threat Appraisal on Protection Motivation	0,6
weight of livelihood costs = weight of ease of engagement with hygienic behaviour	,6
Relative weight of fatigue	,6
maximum effect of hygiene on risk reduction	,13
SWITCH Contact Tracing Activated	1 (ON)
over time contacts tested per tested positive	baseline
effectiveness of identification (contact tracing)	,10
Testing Capacity daily addition	200 (tests per day)
Testing smooth time	7 days
Tested fractional contacts adjustment = Hospitalised fractional contacts adjustment	,0145
Symptomatic fractional contacts adjustment	,5
Baseline contact rate	10

APPENDIX 2: Results of Sensitivity Analysis

Testing and Infectivity Modules

Variable	Value	Range	Sensitive	Comments?
Severe fractional contacts	,0145	,007-,5	N	
Tested fractional contacts	,0145	,007-,5	YES	Higher fraction of contacts leads to higher overall infections
Symptomatic fractional contacts	,1	,05-,5	YES	Higher fraction of contacts leads to higher overall infections
Maximum test rate SI	,45	,25-,85	YES	Higher first peak, however not much difference at the second peak
Maximum test rate CCI	,85	,6-1	N	This is however a "bold" insensitivity – patients in Critical Care, tested or not, are reducing their contacts to a very large degree (they are directly assumed to be positive & enter quarantine).
Maximum test rate HI	,65	,35-,9	N	The same point as above holds here as well. However, we do see some further sensitivity in this parameter when Contact Tracing is activated. In this case, the more we test, the more contacts we can trace & isolate & thus New Infections are reduced. By deactivating Contact Tracing, this parameter is largely insensitive

Behavioural Module

Variable	Value	Range	Sensitive	Comments?
Governmental Response				
Time to perceive changes in trend	14	7-21	N	
Averaging time for perception of trend	14	7-21	N	
Delay in Efficacy communication relative to Threat comminication	4	0,5-7	YES	

time to get and report test results	3	1-7	N	
Population Perceptions of Top-Down Message and Observations				
Time to perceive reported cases	2	1-7	N	
Time to report and perceive deaths and hospitalisations	3	1-7	N	
time to discount a case facing severe consequences	7	3,5-21	YES	Only at lower region: from 7 days up no difference
time to perceive Top Down message	2	1-7	VL	
Bottom-Up Structure				
Avg people reached by one news article	125	60-250	N	
fraction of connections that interact with shared information	,2	,1-,4	YES	Effect of changes most significant in the response of the initial wave (higher interactions lead to faster response)
Avg connections information is shared with	125	60-250	YES	As above.
probability of sharing information per person	,15	,05-,4	YES	As above
Max fraction of Aware that can become Active	,9	,5-1	N	
normal information infection duration	7	3,5-14	VL	
normal information fatigue duration	14	7-31	N	
fraction of TopDown Threat Related message replicated in BottomUp Communications	,5	,25-,85	N	
fraction of TopDown Efficacy Related message replicated in BottomUp Communications	,5	,25-,85	N	
Time to communicate own Appraisals	7	3,5-14	N	
Threat Appraisals				
Contribution of Observations in Threat Assessments	,5	,25 - ,8	L	(higher values lead to more delayed response & faster “return to normal”)

relative contribution bottom up msg in Threat Assessments	,4	,2-,8	N	
Weight on severity for Threat Appraisal	,5	,25-,75	L	Higher values sustain Protection Motivation longer but, at second wave, higher values lead to slower response
Time to Update Threat Appraisal	3	1-14	YES	Slower and Lower Protection Motivation resulting in slower and lower behavioural responses (and thus higher Infected fraction of the population)
time to discount Threat Appraisal	31	14-62	(VL)	
Efficacy Appraisal				
Contribution of Observations in Efficacy Assessments	,5	,25 - ,8	N (VVL)	
relative contribution bottom up msg in Efficacy Assessment	,4	,2-,8	N	
Time to Update Efficacy Appraisal	3	1-14	YES	Slower and Lower Protection Motivation resulting in slower and lower behavioural responses (and thus higher Infected fraction of the population)
time to discount Efficacy Appraisal	42	21-84	Y	(only at lowest region)
time to perceive avg prophylactic response of the population	7	3,5-14	N	
Protection Motivation & relationship with Costs				
relative contribution of Threat Appraisal on Protection Motivation	,6	,3-,8	YES	Slower response and, more importantly, faster recovery.
effect of relative Efficacy levels on Protection Motivation	table	More and Less steep	YES	
effect of the difference between Protection Motivation & Costs on mobility reduction	table	More and Less steep	YES	

Effect of difference between Protection Motivation & Costs on level of adoption of hygienic behaviour	table	More and Less steep	YES	
Costs				
weight of livelihood costs	,6	,3-,8	YES	Faster response since those costs are hypothesised to decrease fast – effect is diminished for subsequent waves as costs remain at average – average to low levels
weight of ease of engagement with other hygienic behaviour	,6	,3-,8	YES	As above, however here effect not diminished over time since ease of engagement with other hygiene behaviour is assumed to remain high
Relative weight of fatigue	,6	,3-,8	YES	Higher relative weight of fatigue increases intensity of mobility reduction and other hygienic measures but, as fatigue "sets in", higher weight leads to lower engagement (the sensitivity is amplified because of the effects of imitation)
costs due to fatigue from social isolation	table	Linear and slower	YES	Higher costs lead to lower adoption of the behaviour
costs due to fatigue from hygienic behaviour	table	faster and Linear	YES	Higher costs lead to lower adoption of the behaviour
Time to perceive behaviour of others	7	3,5-14	N (VVL)	
time to perceive changes in livelihood costs	3	1-7	L	
time to perceive changes in ease of other hygienic behaviour	3	1-7	N	
time to update perception of recent hygienic behaviour intensity	30	14-60	N	
time to update perception of recent distancing intensity	30	14-60	N	
expected average prophylactic response of the population	table	linear	YES	

Appendix 3: Model Documentation

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Behavioural Module
********** Behavioural_Model.Bottom_Up_Information_Dissemination: **********
Behavioural_Model.Actively_Aware(t) = Actively_Aware(t - dt) + (becoming_actively_aware_1 + becoming_actively_aware_after_recovery - rate_of_fatigue) * dt
INIT Behavioural_Model.Actively_Aware = 0
UNITS: Persons
DOCUMENT: The population that is Aware and Active. Aims to represent people that actively interact with and disseminate information and opinions about the virus. This stock increases as people become actively aware and dicreases through a recovering rate as novelty of the situation is lost and people get tired of actively interacting with information.
INFLOWS:
Behavioural_Model.becoming_actively_aware_1 = (Aware*Max_fraction_of_Aware_that_can_become_Active)*effect_of_Susceptibility_Assessment_on_fraction_becoming_actively_aware
UNITS: person/day
DOCUMENT: the rate at which people become actively aware. The people that can become Actively Aware are the product of those who are Aware and the maximum possible daily fraction of people becoming Actively Aware. The movement of this population is then controlled by the effect of the Risk Perception on their movement to Active Aware state
Behavioural_Model.becoming_actively_aware_after_recovery = (Recovered*Max_fraction_of_Aware_that_can_become_Active)* effect_of_Susceptibility_Assessment_on_fraction_becoming_actively_aware_reinfection
UNITS: person/day
DOCUMENT: The rate at which people become actively aware after having been in the second stage of awareness. The people that can become Actively Aware are the product of those who are Aware at Stage 2 and the maximum possible daily fraction of people becoming Actively Aware. The movement of this population is then controlled by the effect of the Risk Perception on their movement to Active Aware state

OUTFLOWS:
Behavioural_Model.rate_of_fatigue = Actively_Aware/Information_Infection_Duration
UNITS: person/day
DOCUMENT: The rate of recovering from the stage of Active Awareness. People are expected to lose interest over some time or simply get tired of interacting with information. The rate is controlled by the number of people who are Actively Aware and the information infection duration
Behavioural_Model.avg_connections_information_is_shared_with = 125
UNITS: people
DOCUMENT: The average number of connections one person shares the information with. It is assumed to be 125 people per person that view the shared information (without considering here whether they interact with it or not)
Behavioural_Model.avg_people_reached_by_one_news_article = 125
UNITS: people/mentions
DOCUMENT: The average number of people that can be reached by one mention of COVID-19 by media. Assumed to be 125 people
Behavioural_Model.Aware(t) = Aware(t - dt) + (Information_infection_rate - becoming_actively_aware_1) * dt
INIT Behavioural_Model.Aware = 0
UNITS: Persons
DOCUMENT: The people who are Aware of COVID-19. It represents people who have received and interacted with information about the virus, without consideration of what their opinions are about it.
INFLOWS:
Behavioural_Model.Information_infection_rate = MAX(0; Fraction_Unaware_1* (Initial_Information_rate_through_media+ (rate_of_interaction_with_shared_information*(1-overlap_in_sharing_1))))
UNITS: person/day
DOCUMENT: The rate at which individuals become "infected" with information regarding COVID-19. Both the initial information rate through media & the information from active sharing by the population contribute so that the fraction of population that remains unaware becomes "infected" with information. As the same people can be reached by both information mechanisms, an overlap in sharing is utilised to account for people that are exposed to both (formulation described in Jalali, Ashouri, Herrera-Restrepo, & Zhang, 2016). A MAX function is used to ensure that this flow cannot go negative (Aware people cannot return back to an "Unaware" state)
OUTFLOWS:
Behavioural_Model.becoming_actively_aware_1 = (Aware*Max_fraction_of_Aware_that_can_become_Active)*effect_of_Susceptibility_Assessment_on_fraction_becoming_actively_aware
UNITS: person/day

DOCUMENT: the rate at which people become actively aware. The people that can become Actively Aware are the product of those who are Aware and the maximum possible daily fraction of people becoming Actively Aware. The movement of this population is then controlled by the effect of the Risk Perception on their movement to Active Aware state
Behavioural_Model."COVID-19_mentions_in_local_news_sources" = GRAPH(TIME)
Points(145): (0,0, 1), (1,0, 0), (2,0, 0), (3,0, 0), (4,0, 0), (5,0, 0), ...
UNITS: mentions
DOCUMENT: Mentions of COVID-19 in norwegian newspapers, tv and radio, and web sources (Retriever: Atekst, 2020)
Behavioural_Model.effect_of_Severity_Assessment_on_Information_Infection_Duration = GRAPH(Total_Severity_Assessment)
Points(11): (0,000, 1,01338570185), (0,100, 1,03597241992), (0,200, 1,09485174636), (0,300, 1,23840584404), (0,400, 1,53788284274), (0,500, 2,000), ...
UNITS: dmnl
DOCUMENT: The effect that the Perceived Severity has on how long an average individual will remain actively aware. At very low levels of Severity, this effect is assumed to be 1 so the individual "recovers" at the normal time. At higher levels of Perceived Severity, a person is assumed to recover at slower rates (a duration that increases above the normal value) as the information is more engaging or perceived as more significant. The maximum possible effect expected at the highest levels of Perceived Severity is 3 times the normal infection duration: even if the Severity is very high, people will still become fatigued and will start avoiding information albeit at a slower rate
Behavioural_Model.effect_of_Susceptibility_Assessment_on_fraction_becoming_actively_aware = GRAPH(Susceptibility_Assessment)
Points(11): (0,000, 0,0000), (0,100, 0,395317488847), (0,200, 0,617542228657), (0,300, 0,742464187276), (0,400, 0,812688122554), (0,500, 0,852163977242), ...
UNITS: dmnl
DOCUMENT: The effect of the Susceptibility Assessment on peoples' movement to an Active Awareness state. The effect is expected to be non-linear and increasing more steeply in the lower regions and saturate in the higher regions. At low levels of perceived Susceptibility to the virus, very few people become Active Aware but as the Susceptibility Assessment increases, it leads to higher increases in the fraction of people that are expected to move to the next stage. The upper bounds of the distribution are lower than 1 to capture that, even if the Susceptibility Assessment is at the highest possible level, a small fraction of the population will still resist the information.
Behavioural_Model.effect_of_Susceptibility_Assessment_on_fraction_becoming_actively_aware_reinfection = GRAPH(Susceptibility_Assessment)
Points(11): (0,000, 0,0000), (0,100, 0,0000), (0,200, 0,0096), (0,300, 0,0574), (0,400, 0,1676), (0,500, 0,3351), ...
UNITS: dmnl

DOCUMENT: The effect of the Susceptibility Assessment on peoples' movement to an Active Awareness state. This effect is non-linear and represented by an S-Shaped curve. At low levels of perceived Susceptibility to the virus, very few people become Active Aware but as the Susceptibility Assessment increases, a higher fraction is expected to move. The upper bounds of the distribution are lower than 1 to capture that, even if the Susceptibility Assessment is at the highest possible level, a small fraction of the population will still resist the information. Compared to the similar effect of Susceptibility Assessment on fraction becoming actively aware, here, we hypothesise that population that has been in the past Active Aware and has Recovered is has a higher threshold or becoming again Active and is more "slow" to reinfection at the lower ranges or Susceptibility Assessment
Behavioural_Model.Fatigued(t) = Fatigued(t - dt) + (rate_of_fatigue - becoming_aware_stage_3) * dt
INIT Behavioural_Model.Fatigued = 0
UNITS: Persons
DOCUMENT: The people that experience Information Fatigue after having been Actively Aware. These people are still expected to somewhat interact and share information but at a much lower rate at this stage. People are expected to recover from this information fatigueness after some time and become again Aware but on the "second stage" of awareness
INFLOWS:
Behavioural_Model.rate_of_fatigue = Actively_Aware/Information_Infection_Duration
UNITS: person/day
DOCUMENT: The rate of recovering from the stage of Active Awareness. People are expected to lose interest over some time or simply get tired of interacting with information. The rate is controlled by the number of people who are Actively Aware and the information infection duration
OUTFLOWS:
Behavioural_Model.becoming_aware_stage_3 = Fatigued/normal_information_fatigue_duration
UNITS: person/day
DOCUMENT: the rate at which people that have been fatigued from information return to a second stage of awareness. Given by the number of fatigued people over a duration of "immunity", the average time that they will remain fatigued.
Behavioural_Model.fraction_of_connections_that_interact_with_shared_information = ,2
UNITS: dmnl/day
DOCUMENT: The fraction of connections or people exposed to a media circulated mention that actually engage with the presented information. It is assumed to be 20%.
Behavioural_Model.Fraction_Unaware_1 = Unaware/(NORWAY_Population)
UNITS: dmnl
DOCUMENT: Fraction of initial population remaining susceptible to information acquisition.
Behavioural_Model.information_dissemination_weight_of_Active_Aware = ,8
UNITS: dmnl

DOCUMENT: The weight, or contribution, that an Active Aware person has on information dissemination. Active Aware individuals are the main content creators and distributors with an assumed 80% contribution in content.
Behavioural_Model.information_dissemination_weight_of_Aware = ,05
UNITS: dmnl
DOCUMENT: The weight, or contribution, that an Aware person has on information dissemination. Aware people are not considered to create and share much content but mainly see the information and only very occasionally contribute themselves. This contribution is assumed here to be 5%.
++++
Behavioural_Model.information_dissemination_weight_of_Fatigued = ,05
UNITS: dmnl
DOCUMENT: The weight, or contribution, that an information Fatigued person has on information dissemination. Fatigued people are not considered to create and share much content. We hypothesise that their contribution is the same as that of the Aware at a 5%.
Behavioural_Model.information_dissemination_weight_of_Recovered = ,1
UNITS: dmnl
DOCUMENT: The weight, or contribution, that a person in the second stage of being Active Aware has on information dissemination. An average Recovered individual is expected to contribute somewhat to information dissemination and the value of 10% is chosen here
Behavioural_Model.Information_Infection_Duration = normal_information_infection_duration*effect_of_Severity_Assessment_on_Information_Infection_Duration
UNITS: Days
DOCUMENT: Duration of information infection. This duration is not considered fixed but the normal information infection duration is adjusted due to the effect of the Perception of the Severity of the virus.
Behavioural_Model.Initial_Information_rate_through_media = "COVID-19_mentions_in_local_news_sources"*avg_people_reached_by_one_news_article*fraction_of_connections_that_interact_with_shared_information
UNITS: person/day
DOCUMENT: The rate at which individuals receive information due to mass media communications. It is the product of the actual mentions in local news sources, the number of people that can be reached per mention, and the fraction of those people that are assumed to actually interact with this information.
Behavioural_Model.Max_fraction_of_Aware_that_can_become_Active = ,9
UNITS: Per Day
DOCUMENT: the maximum fraction of people who are aware that can become actively aware per day. We exclude a 10% of the Aware population to capture people who are either resistant of cannot access the information.
Behavioural_Model.normal_information_fatigue_duration = 31
UNITS: days

DOCUMENT: The normal duration of fatigue is assumed to be 1 month. After this average period, individuals can recover from the "information overload".
Behavioural_Model.normal_information_infection_duration = 7
UNITS: days
DOCUMENT: The normal duration of infection by an information before a person becomes fatigued. It is assumed to be one week.
Behavioural_Model.NORWAY_Population = 5367580
UNITS: Persons
DOCUMENT: As of February 27th 2020. Source: Statistisk Sentralbyrå (SSB) https://www.ssb.no/en/befolkning/statistikker/folkemengde
Behavioural_Model.overlap_in_sharing_1 = ,5
UNITS: dmnl
Behavioural_Model.probability_of_sharing_information_per_person = ,15
UNITS: dmnl/person
DOCUMENT: The probability for an average person to share information. Assumed to be constant and at 15%
Behavioural_Model.rate_of_interaction_with_shared_information = avg_connections_information_is_shared_with*fraction_of_connections_that_interact_with_shared_information*(total_sharing_1)
UNITS: Persons/Day
DOCUMENT: The rate of peoples' interactions with shared information. The product of the total sharing and the average connections shared with gives us the "spread" of the information: how many people it can potentially reach. This number is adjusted by the fraction of connections that interact with information to give us the actual number of people per day that have access to and interact with the information.
Behavioural_Model.rate_of_interaction_with_shared_information_reference_time = 6360000*0 + 7450000*1 + 6850000*0
UNITS: Persons/Day
DOCUMENT: The rate of peoples' interactions with shared information at the reference time. The value has been determined from the partial model testing of the behavioural model (that is, based on the behaviour of the model when infection-related data are used).
Behavioural_Model.Recovered(t) = Recovered(t - dt) + (becoming_aware_stage_3 - becoming_actively_aware_after_recovery) * dt
INIT Behavioural_Model.Recovered = 0
UNITS: Persons
DOCUMENT: The people who are Aware of COVID-19 but have been previously Actively Aware. It represents people who have gone through a stage of Active "alertness", have "taken a break", and are now again aware of the situation. Those people can again become once again Active Aware from this stage.
INFLOWS:
Behavioural_Model.becoming_aware_stage_3 = Fatigued/normal_information_fatigue_duration

UNITS: person/day
DOCUMENT: the rate at which people that have been fatigued from information return to a second stage of awareness. Given by the number of fatigued people over a duration of "immunity", the average time that they will remain fatigued.
OUTFLOWS:
Behavioural_Model.becoming_actively_aware_after_recovery = (Recovered*Max_fraction_of_Aware_that_can_become_Active)* effect_of_Susceptibility_Assessment_on_fraction_becoming_actively_aware_reinfection
UNITS: person/day
DOCUMENT: The rate at which people become actively aware after having been in the second stage of awareness. The people that can become Actively Aware are the product of those who are Aware at Stage 2 and the maximum possible daily fraction of people becoming Actively Aware. The movement of this population is then controlled by the effect of the Risk Perception on their movement to Active Aware state
Behavioural_Model.relative_to_time_of_survey_rate_of_interaction_with_shared_information = rate_of_interaction_with_shared_information/rate_of_interaction_with_shared_information_reference_time
UNITS: dmnl
DOCUMENT: The, relative to the reference time, rate of interaction with shared information via the Bottom Up mechanism is given as the ratio of the current rate of interaction over the rate of interaction at the reference time.
Behavioural_Model.total_sharing_1 = Weighted_Aware*probability_of_sharing_information_per_person
UNITS: dmnl
DOCUMENT: Total expected sharing behaviour of the aware population. Given by the weighted population and the average probability per person to create or share information.
Behavioural_Model.Unaware(t) = Unaware(t - dt) + (- Information_infection_rate) * dt
INIT Behavioural_Model.Unaware = NORWAY_Population
UNITS: Persons
DOCUMENT: Population that is unaware of COVID-19 and thus Susceptible to receive relevant information. It decreases as indicviduals become aware of the virus (or "infected" with information).
OUTFLOWS:
Behavioural_Model.Information_infection_rate = MAX(0; Fraction_Unaware_1* (Initial_Information_rate_through_media+ (rate_of_interaction_with_shared_information*(1-overlap_in_sharing_1))))
UNITS: person/day
DOCUMENT: The rate at which individuals become "infected" with information regarding COVID-19. Both the initial information rate through media & the information from active sharing by the population contribute so that the fraction of population that remains unaware becomes "infected" with information. As the same people can be reached by both information mechanisms, an overlap in sharing is utilised to account for people that are exposed to both (formulation described in Jalali, Ashouri, Herrera-Restrepo, & Zhang, 2016).

A MAX function is used to ensure that this flow cannot go negative (Aware people cannot return back to an "Unaware" state)
Behavioural_Model.Weighted_Aware = (Aware*information_dissemination_weight_of_Aware) + (Actively_Aware*information_dissemination_weight_of_Active_Aware) + (Fatigued*information_dissemination_weight_of_Fatigued) + (Recovered*information_dissemination_weight_of_Recovered)
UNITS: people
DOCUMENT: The number of people who are aware of COVID-19, weighted according to their expected contributions in information creation and dissemination.
********** Behavioural_Model.Calculations_of_Values_at_reference_time: **********
Behavioural_Model.average_Efficacy_Apprasail_reference_time = (avg_reported_risk_reduction_SELF_by_following_advice_reference+avg_reported_risk_reduction_OTHERS_by_following_advice_reference)/2
UNITS: Dmnl
DOCUMENT: The average assessment of the efficacy of the proposed measures at the reference time captures peoples' evaluations of how much the proposed measures would reduce the risk of infection. It is given as the average perceived risk reduction for the self and that for others, as captured during the reference time.
Behavioural_Model.average_optimism_bias = (optimism_bias_for_risk_survey_data+optimism_bias_for_worry_survey_data+optimism_bias_for_efficacy_survey_data)/3
UNITS: Dmnl
DOCUMENT: Optimism bias is “the belief that bad things are less likely to befall oneself than others” (van Bavel et al., 2020, p. 461) that can make people underestimate the probability of a negative outcome such as becoming infected for themselves (Sharot, 2011). Optimism bias has been reported in the COVID-19 response in both USA (Wise, Zbozinek, Michelini, Hagan, & Mobbs, 2020) and Norway (Sætrevik, 2020). We use the average relative difference in risk and efficacy cognitions for others and for the self to get an estimate of the average magnitude of the optimism bias.
Behavioural_Model.average_Severity_Assessment_time_of_survey = (severity_OTHERS_time_of_Survey+avg_severity_of_consequences_of_infection_SELF_reference)/2
UNITS: Dmnl
DOCUMENT: The average Severity assessment at the reference time represents the severity of consequences if one gets infected with COVID-19. It is given as the average severity perception for the self and that for others, as captured during the reference time.
Behavioural_Model.average_Susceptibility_Assessment_reference_time = (avg_risk_of_infection_SELF_reference+avg_risk_of_infection_OTHERS_reference)/2
UNITS: Dmnl

DOCUMENT: The average Susceptibility assessment at the reference time, representing the assessment of the risk of contracting COVID-19, is given as the average risk of infection for the self and that for others, as captured during the reference time.
Behavioural_Model.average_Threat_Appraisal_reference_time = (avg_worry_of_getting_infected_SELF_reference+avg_worry_of_family_getting_infected_reference)/2
UNITS: Dmnl
DOCUMENT: The average reported "worry" that oneself or one's family member will contract COVID-19 is considered as a proxy for the individual's Threat Appraisal; their perception of how threatening the virus is to one's well-being.
Behavioural_Model.BU_msg_contribution_efficacy_reference_time = Contribution_of_Bottom_Up_message_on_Threat_Appraisals*average_Efficacy_Apprasail_reference_time*0 + Contribution_of_Bottom_Up_message_on_Efficacy_Appraisals*average_Efficacy_Apprasail_reference_time
UNITS: dmnl
Behavioural_Model.BU_msg_contribution_Severity_Assessment_reference_time = Contribution_of_Bottom_Up_message_on_Threat_Appraisals*average_Severity_Assessment_time_of_survey
UNITS: dmnl
DOCUMENT: The contribution of the Bottom-Up message to Severity Perceptions at the reference time is the product of the value of the Severity Assessment at the reference time and the relative contribution of Bottom-Up messages on Threat-Related Assessments
Behavioural_Model.BU_msg_contribution_Susceptibility_reference_time = Contribution_of_Bottom_Up_message_on_Threat_Appraisals*average_Susceptibility_Assessment_reference_time
UNITS: dmnl
DOCUMENT: The contribution of the Bottom-Up message to Susceptibility Perceptions at the reference time is the product of the value of the Susceptibility Assessment at the reference time and the relative contribution of Bottom-Up messages on Threat-Related Assessments
Behavioural_Model.cases_contribution_EFFICACY_reference_time = Contribution_of_Observations_on_Threat_Appraisals*average_Efficacy_Apprasail_reference_time*0 + Contribution_of_Observations_on_Efficacy_Appraisals*average_Efficacy_Apprasail_reference_time
UNITS: dmnl
Behavioural_Model.cases_contribution_Severity_reference_time = Contribution_of_Observations_on_Threat_Appraisals*average_Severity_Assessment_time_of_survey
UNITS: dmnl
DOCUMENT: The contribution of information about the actual number of severe cases to Severity Perceptions at the reference time is the product of the value of the Severity Assessment at the reference time and the relative contribution of Actual cases on Threat-Related Assessments

Behavioural_Model.cases_contribution_Susceptibility_reference_time = Contribution_of_Observations_on_Threat_Appraisals*average_Susceptibility_Assessment_reference_time
UNITS: dmnl
DOCUMENT: The contribution of information about the actual number of cases to Susceptibility Perceptions at the reference time is the product of the value of the Susceptibility Assessment at the reference time and the relative contribution of Actual cases on Threat-Related Assessments
Behavioural_Model.Contribution_of_Bottom_Up_message_on_Efficacy_Appraisals = (1-Contribution_of_Observations_on_Efficacy_Appraisals)*relative_contribution_bottom_up_msg_in_Efficacy_Appraisals {well.. a) some proportion of msgs are misinformation or in oposite direction b) again, some relative value?}
UNITS: dmnl
DOCUMENT: The degree to which peoples' Efficacy assessments are influenced by Bottom-Up messages. It is given as the product of the inverse of the contribution of observations and the relative contribution of the bottom-up message. The relationship between those weight variables is multiplicative as whatever fraction remains from the contribution of observations is split between top-and bottom-up message and the bottom-up message receives a fraction of this remainder equal to its relative contribution.
Behavioural_Model.Contribution_of_Bottom_Up_message_on_Threat_Appraisals = (1-Contribution_of_Observations_on_Threat_Appraisals)*relative_contribution_bottom_up_msg_in_Threat_Appraisals {well.. a) some proportion of msgs are misinformation or in oposite direction b) again, some relative value?}
UNITS: dmnl
DOCUMENT: The degree to which peoples' Threat-Related perceptions are influenced by Bottom-Up messages. It is given as the inverse of the contribution of actual cases and the relative contribution of the bottom-up message. The relationship between those weight variables is multiplicative as whatever fraction remains from the contribution of the actual cases is split between top-and bottom-up message and the bottom-up message receives a fraction of this remainder equal to its relative contribution.
Behavioural_Model.Contribution_of_Observations_on_Efficacy_Appraisals = ,5 {Not sure if this should be constant here - perhaps more focus on projections at some stages}
UNITS: dmnl
DOCUMENT: The contribution, or weight that observations related to the efficacy of the response have to an individual's Efficacy Appraisal (their perception of the overall efficiency of the proposed response to mitigate the risk). It is hypothesised to be 40%, somewhat lower than the similar mechanism for the case of Threat-Related Assessment (see variable "Contribution of ACTUAL CASES on Threat-Related Assessments"). While observations are important, we generally expect that people might not perceive themselves as knowledgeable enough to rely as heavily on their own perceptions of the response's efficacy but, rather, would place more weight on information dissemination from Top-Down, as well as Bottom-Up mechanisms.
Behavioural_Model.Contribution_of_Observations_on_Threat_Appraisals = ,5 {Not sure if this should be constant here - perhaps more focus on projections at some stages}
UNITS: dmnl

DOCUMENT: The contribution, or weight of the Actual cases to the Threat-Related assessments is hypothesised to be rather high, taking 50% - Practically, this means that 50% of peoples' Threat-Related assessments are influenced by information regarding the actual cases.
Behavioural_Model.Contribution_of_Top_Down_message_on_Efficacy_Appraisals = (1-Contribution_of_Observations_on_Efficacy_Appraisals)*(1-relative_contribution_bottom_up_msg_in_Efficacy_Appraisals) {SOME connection here with trust in government I would imagine}
UNITS: dmnl
DOCUMENT: The degree to which peoples' Efficacy assessments are influenced by Top-Down messages. The fractional contribution of the Top-Down message is given as the inverse of the contribution of actual observations and that of the relative contribution of the bottom-up message. The relationship between those weight variables is multiplicative as whatever fraction remains from the contribution of observations is split between top-and bottom-up message and the top-down message receives the inverse fraction (whatever "remains") of that of the bottom-up message.
Behavioural_Model.Contribution_of_Top_Down_message_on_Threat_Appraisals = (1-Contribution_of_Observations_on_Threat_Appraisals)*(1-relative_contribution_bottom_up_msg_in_Threat_Appraisals) {SOME connection here with trust in government I would imagine}
UNITS: dmnl
DOCUMENT: The degree to which peoples' Threat-related assessments are influenced by Top-Down messages. The fractional contribution of the Top-Down message is given as the inverse of the contribution of actual cases and that of the relative contribution of the bottom-up message. The relationship between those weight variables is multiplicative as whatever fraction remains from the contribution of the actual cases is split between top-and bottom-up message and the top-down message receives the inverse fraction (whatever "remains") of that of the bottom-up message.
Behavioural_Model.max_multiplier_Efficacy_Related_Assessments = Contribution_of_Observations_on_Efficacy_Appraisals/cases_contribution_EFFICACY_reference_time
UNITS: dmnl
DOCUMENT: This variable represents a calculation of the maximum possible multiplier for Efficacy assessment. Its use is to help us determine the maximum effects of the different contributors to Efficacy Appraisals to ensure robustness of the model.
Behavioural_Model.max_multiplier_Threat_Related_Assessments = Contribution_of_Observations_on_Threat_Appraisals/cases_contribution_Severity_reference_time
UNITS: dmnl
DOCUMENT: This variable represents a calculation of the maximum possible multiplier for Threat-Related assessment. Its use is to help us determine the maximum effects of the different contributors to the Threat Appraisals to ensure robustness of the model.
Behavioural_Model.optimism_bias_for_efficacy_survey_data = avg_reported_risk_reduction_OTHERS_by_following_advice_reference/avg_reported_risk_reduction_SELF_by_following_advice_reference

UNITS: Dmnl
Behavioural_Model.optimism_bias_for_risk_survey_data = avg_risk_of_infection_OTHERS_reference/avg_risk_of_infection_SELF_reference
UNITS: dmnl
DOCUMENT: For a definition of "optimism bias", see the documentation of the variable "average optimism bias". This variable calculates the relative magnitute of the perceived probability that an average person would get infected relative to that of oneself getting infected.
Behavioural_Model.optimism_bias_for_worry_survey_data = avg_worry_of_family_getting_infected_reference/avg_worry_of_getting_infected_SELF_reference
UNITS: dmnl
DOCUMENT: For a definition of "optimism bias", see the documentation of the variable "average optimism bias". This variable calculates the relative magnitute of the perceived worry that a family member will contract the disease relative to that for the self.
Behavioural_Model.relative_contribution_bottom_up_msg_in_Efficacy_Appraisals = ,4
UNITS: dmnl
DOCUMENT: This parameter represents the fractional weight, the fractional significance of the bottom-up message relative to the top-down message. Is is hypothesised that the bottom-up message has 40% of contribution (thus leaving the remaining 60% to the top-down message).
Behavioural_Model.relative_contribution_bottom_up_msg_in_Threat_Appraisals = ,4
UNITS: dmnl
DOCUMENT: This parameter represents the fractional weight, the fractional significance of the bottom-up message relative to the top-down message. Is is hypothesised that the bottom-up message has 40% of contribution (thus leaving the remaining 60% to the top-down message).
Behavioural_Model.severity_OTHERS_time_of_Survey = average_optimism_bias*avg_severity_of_consequences_of_infection_SELF_reference
UNITS: dmnl
DOCUMENT: There are no explicit data for perceptions of how severe the consequences of infection would be for an average person in the datareported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). We multiply the average optimism bias with the perceptions of how severe the consequences of COVID-19 would be for the self in order to estimate the perceptions of this severity for an average person.
Behavioural_Model.TD_msg_Total_contribution_EFFICACY_reference_time = Contribution_of_Top_Down_message_on_Threat_Appraisals*average_Efficacy_Apprasail_reference_time* 0 + Contribution_of_Top_Down_message_on_Efficacy_Appraisals*average_Efficacy_Apprasail_reference_time
UNITS: dmnl
Behavioural_Model.TOP_DOWN_communication_Total_contribution_on_Severity_at_reference_time = Contribution_of_Top_Down_message_on_Threat_Appraisals*average_Severity_Assessment_time_of_survey
UNITS: dmnl

DOCUMENT: The contribution of the Top-Down message to Severity Perceptions at the reference time is the product of the value of the Severity Assessment at the reference time and the relative contribution of Top-Down messages on Threat-Related Assessments
Behavioural_Model.TOP_DOWN_communication_Total_contribution_on_Susceptibility_at_reference_time = Contribution_of_Top_Down_message_on_Threat_Appraisals*average_Susceptibility_Assessment_reference_time
UNITS: dmnl
DOCUMENT: The contribution of the Top-Down message to Susceptibility Perceptions at the reference time is the product of the value of the Susceptibility Assessment at the reference time and the relative contribution of Top-Down messages on Threat-Related Assessments
Behavioural_Model.weight_on_severity_for_threat_Appraisal = ,5
UNITS: dmnl
DOCUMENT: Severity and Risk might not contribute equally to the assessment of the Threat. Without having any evidence of their relative contributions, we assume an equal weight on both perceptions.
Behavioural_Model.Weighted_Threat_Appraisal_at_reference_time = (weight_on_severity_for_threat_Appraisal*average_Severity_Assessment_time_of_survey) + (1-weight_on_severity_for_threat_Appraisal)*average_Susceptibility_Assessment_reference_time
UNITS: dmnl
********** Behavioural_Model.Case_and_Death_Counts: **********
Behavioural_Model."10th_case" = IF Testing.Cumulative_Positive_Tests > 9,5 AND Testing.Cumulative_Positive_Tests < 10,5 THEN 1 ELSE 0
UNITS: day
Behavioural_Model."10th_death" = IF Main_Infection_Model.ALL_DEAD > 9,5 AND Main_Infection_Model.ALL_DEAD <10,5 THEN 1 ELSE 0
UNITS: day
Behavioural_Model."1st_case" = IF Testing.Cumulative_Positive_Tests > 0,7 AND Testing.Cumulative_Positive_Tests < 1,3 THEN 1 ELSE 0
UNITS: day
Behavioural_Model."1st_Death" = IF Main_Infection_Model.ALL_DEAD > 0,7 AND Main_Infection_Model.ALL_DEAD < 1,3 THEN 1 ELSE 0
UNITS: day
********** Behavioural_Model.Government:_Threat_&_Efficacy_Communication_Message: **********

Behavioural_Model."Actual_SharedTotal_Top-Down_Efficacy_Related_communication_message" = SMTH1("Total_Top-Down_Efficacy_Related_communication_message"; Delay_in_Efficacy_communication_relative_to_Threat_comminication; 0) {IF Converter_198> 0 THEN MIN(1; SMTH1(Converter_198; delay_in_efficacy_communication_relative_to_that_of_risk_2; 0)) ELSE 0} {DELAY CONVERTER}
INIT Behavioural_Model."Actual_SharedTotal_Top-Down_Efficacy_Related_communication_message" = 0
UNITS: dmnl
Behavioural_Model.ADDITIONAL_TOP_DOWN_EFFICACY_COMMUNICATION_SWITCH = 1
UNITS: dmnl
DOCUMENT: This is a Switch that activates a mechanism of additional (or more "sensitive") decision mechanism for the communication of efficacy. This mechanism is ON, when the Switch takes the value of 1 and OFF at the value of 0
Behavioural_Model.ADDITIONAL_TOP_DOWN_THREAT_COMMUNICATION_SWITCH = 1
UNITS: dmnl
DOCUMENT: This is a Switch that activates a mechanism of additional (or more "sensitive") decision mechanism for the communication of Threat-Related information. This mechanism is ON, when the Switch takes the value of 1 and OFF at the value of 0
Behavioural_Model.averaging_time_for_perception_of_trend = 14
UNITS: days
DOCUMENT: The averaging time during which the government looks at the development of new cases in order to establish the pattern, or trend, of growth in the new cases. It is assumed to be 7 days
Behavioural_Model.DATA_New_Reported_Cases_per_10000_SUSC_Time_of_Survey = ,475*0 + ,453
UNITS: People/ten thousand people/Day
DOCUMENT: Norwegian Institute of Public Health - FHI (2020)
Behavioural_Model.Delay_in_Efficacy_communication_relative_to_Threat_comminication = 4
UNITS: days
DOCUMENT: The government might strive to provide information of Risk and Efficacy at the same time/message, or there might be some delay between the two types of messages (represented here simply as an information delay). The strength of the Efficacy message is controlled by the Risk Message & its relative increase.
+++++
Behavioural_Model.effect_of_new_cases_on_governments_communication_message_magnitude = GRAPH(Reported_New_cases_relative_to_reference_time)
Points(13): (0,000, 0,000), (0,250, 0,303), (0,500, 0,582), (0,750, 0,814), (1,000, 1,000), (1,250, 1,157), ...
UNITS: dmnl
DOCUMENT: The effect of the, relative to the reference time, new cases on the government's communication message magnitude. This can be considered as representing a "risk perception" that emerges from the number of new cases. This effect ranges from 0 to 1,55. 0 indicates no communication due to New

Cases and 1,55 is the maximum value this effect can take. The effect is expected to be non-linear and can be read as: If the new daily cases are 0, government's will not communicate any message (value of 0), while if the new cases are 3 times as many as they were over the reference period, the communication is assumed to take its maximum value of 1,55. The shape of the effect indicates that small increases in the number of new cases when those are relative low elicit a larger increase in communication. At higher values of new cases relative to the reference period value, the effect saturates: small changes do not increase the communication decision as much as in the "lower" region. The steepness of the "lower" region we believe is justified due to an already alerted government, expected to be ready to update their communication steeply due to observations.
Behavioural_Model.effect_of_perceived_trend_of_new_cases_growth_on_Top_Down_communication_message = GRAPH(Perceived_by_government_trend_of_growth_of_new_cases)
Points(11): (0,000, 0,000), (0,200, 0,419282164307), (0,400, 0,762561366441), (0,600, 1,04361460612), (0,800, 1,2737215367), (1,000, 1,46211715726), ...
UNITS: dmnl
DOCUMENT: The Perceived growth in new cases impacts government's decision regarding how strong of a communication message on Threat and/or Efficacy they are to share with the population. This shape of this effect describes a steep increase at increases in the perceived tend of new cases growth and a saturation at higher levels.
Behavioural_Model.intensity_of_Efficacy_Related_communication = 1,15
UNITS: dmnl
DOCUMENT: The intensity of Efficacy-Related communication is a parameter to facilitate testing of different policies. In the case of Efficacy communication, our baseline assumption is that governmental agents already place more focus on efficacy communication in their public message (30% more than in Threat-Related communication). A value of 1 would represent equal focus to Threat- and Efficacy-Related messages
Behavioural_Model.intensity_of_Threat_Related_communication = 1
UNITS: dmnl
DOCUMENT: The intensity of Threat-Related communication is a parameter to facilitate testing of different policies. When this parameter has a value of 1, the system operates under the baseline assumptions. Lower or higher values of this parameter aim to represent lower or higher intensity of Threat-Related communication respectively
Behavioural_Model.Perceived_by_government_trend_of_growth_of_new_cases = SMTH1(MIN(1; TREND(Reported_New_Cases_2; averaging_time_for_perception_of_trend)); time_to_perceive_changes_in_trend) {DELAY CONVERTER}
UNITS: Per Day
DOCUMENT: The Perceived growth in new cases by governmental authorities. It is described as a smoothing of the observed trend of new cases over an averaging period.
Behavioural_Model.Reported_New_cases_relative_to_reference_time = (Reported_New_Cases_2/Susc_10000_people_1)/DATA_New_Reported_Cases_per_10000_SUSC_Time_of_Survey
UNITS: dmnl

DOCUMENT: The number of new cases that have been tested and reported to the government per 10000 susceptible are compared here to the number of such cases at the reference period, as given by data from the
Behavioural_Model.time_to_perceive_changes_in_trend = 14
UNITS: days
DOCUMENT: The time for the government to update their perceptions regarding an observed growth in new cases. We have chosen a value of 7 days.
Behavioural_Model.Top_Down_Efficacy_Related_communication_message_due_to_new_cases = effect_of_new_cases_on_governments_communication_message_magnitude*intensity_of_Efficacy_Related_communication
UNITS: Dmnl
DOCUMENT: The Top-Down Efficacy-Related communication message represents efforts of authorities to explicitly address the population through communication messages aiming to raise awareness (e.g. press conferences, pubic addresses, etc.). The Efficacy-Related communication message emphasises what can be done to successfully mitigate the threat posed by COVID-19 and can contain both information about the efficiency of the proposed responses and "emotional" messages aiming to raise the population's perception that "we can fight it". To endogenise this message, we have grounded it on the, perceived by the government, confirmed COVID-19 cases. The contribution of the new cases on government's communication is here modified by a parameter that can allow easier testing of governmental decision rules regarding communication of Efficacy-Related messages. The product of the two gives the government's decision on the magnitude of their Efficacy-Related communication message. The value of this parameter is given relative to the reference time.
Behavioural_Model.Top_Down_Threat_Related_communication_message_due_to_new_cases = effect_of_new_cases_on_governments_communication_message_magnitude*intensity_of_Threat_Related_communication
UNITS: Dmnl
DOCUMENT: The Top-Down Threat-Related communication message represents efforts of authorities to explicitly address the population through communication messages aiming to raise awareness (e.g. press conferences, pubic addresses, etc.). The Threat-Related communication message is that which emphasises how threatening (or "serious") COVID-19 is for peoples' wellbeing. To endogenise this message, we have grounded it on the, perceived by the government, confirmed COVID-19 cases. The contribution of the new cases on government's communication is here modified by a parameter that can allow easier testing of governmental decision rules regarding communication of Threat-Related messages. The product of the two gives the government's decision on the magnitude of their Threat-Related communication message. The value of this parameter is given relative to the reference time.
Behavioural_Model.Total_Top_Down_Threat_Related_communication_message = ADDITIONAL_TOP_DOWN_THREAT_COMMUNICATION_SWITCH* (MAX(Top_Down_Threat_Related_communication_message_due_to_new_cases; effect_of_perceived_trend_of_new_cases_growth_on_Top_Down_communication_message)) + (1-ADDITIONAL_TOP_DOWN_THREAT_COMMUNICATION_SWITCH)*Top_Down_Threat_Related_communication_message_due_to_new_cases {ADDITIONAL_TOPDOWN_COM_SWITCH*

MAX(TD_message_contribution_of_New_Cases_OMIT; trend_of_growth_of_new_cases*WHATEVER) + (1-ADDITIONAL_TOPDOWN_COM_SWITCH)*TD_message_contribution_of_New_Cases_OMIT
UNITS: dmnl
DOCUMENT: This variable aims to utilise an additional mechanism for the government's decision for sharing a Threat-Related communication message. The formulation allows this variable to take a value equal to: (MAX(Top_Down_Threat_Related_communication_message_due_to_new_cases; effect_of_perceived_trend_of_new_cases_growth_on_Top_Down_communication_message)) when the Additional Top Down Communication SWITCH is ON (=1). In this case, the Total Threat-Related communication message will be equal to whichever value is higher (MAX function): that of the Top Down Threat Related communication message due to new cases, or that of the effect of perceived trend of new cases growth on Top Down communication message. If the SWITCH is OFF (=0) then the total message will be equal to the value of the Top Down Threat Related communication message due to new cases.
Behavioural_Model."Total_Top-Down_Efficacy_Related_communication_message" = ADDITIONAL_TOP_DOWN_EFFICACY_COMMUNICATION_SWITCH* (MAX(Top_Down_Efficacy_Related_communication_message_due_to_new_cases; effect_of_perceived_trend_of_new_cases_growth_on_Top_Down_communication_message)) + (1-ADDITIONAL_TOP_DOWN_EFFICACY_COMMUNICATION_SWITCH)*Top_Down_Efficacy_Related_communication_message_due_to_new_cases {ADDITIONAL_TOPDOWN_COM_SWITCH* MAX(TD_message_contribution_of_New_Cases_OMIT; trend_of_growth_of_new_cases*WHATEVER) + (1-ADDITIONAL_TOPDOWN_COM_SWITCH)*TD_message_contribution_of_New_Cases_OMIT
UNITS: dmnl
DOCUMENT: This variable aims to utilise an additional mechanism for the government's decision for sharing an Efficacy-Related communication message. The formulation allows this variable to take a value equal to ((MAX(Top_Down_Efficacy_Related_communication_message_due_to_new_cases; effect_of_perceived_trend_of_new_cases_growth_on_Top_Down_communication_message)) when the Additional Top Down Efficacy Communication SWITCH is ON (=1). In this case, the Total Efficacy-Related communication message will be equal to whichever value is higher (MAX function): that of the Top Down Efficacy Related communication message due to new cases, or that of the effect of perceived trend of new cases growth on Top Down communication message. If the SWITCH is OFF (=0) then the total message will be equal to the value of the Top Down Efficacy Related comminication message due to new cases.
********** Behavioural_Model.Infection_Sector_Data: **********
Behavioural_Model."Data-Based_Susceptible" = Main_Infection_Model.NORWAY_INIT_POP-Main_Infection_Model.Cumulative_Confirmed_Cases_DATA-Main_Infection_Model.Cumulative_Deaths_DATA
UNITS: People
DOCUMENT: The Susceptible population according to the data is given as the total population of Norway minus the infected population and the dead due to covid-19 population

****
Behavioural_Model.Mobility_DATA:
****
Behavioural_Model.DATA_mobility_average_Google = (((retail_and_recreation_fractional_change+transit_stations_fractional_change+workplaces_fractional_change+grocery_and_pharmacy_fractional_change)/4)+100)/100
UNITS: dmnl
DOCUMENT: We assume a quite rough average of all the mobility indicators.
Behavioural_Model.DATA_overall_mobility_fractional_decrease_IHME = GRAPH(TIME)
Points(112): (41,0, 0,0), (42,0, -1,0), (43,0, -1,0), (44,0, -2,0), (45,0, -2,0), (46,0, -3,0), ...
UNITS: dmnl
DOCUMENT: Data on the fraction decrease of the population's mobility from COVID-19 Projections: Social Distancing (Institute for Health Metrics and Evaluation (IHME), 2020)
Behavioural_Model.DATA_overall_mobility_IHME = (DATA_overall_mobility_fractional_decrease_IHME+100)/100
UNITS: dmnl
DOCUMENT: The fractional decrease of mobility is here adjusted to a scale ranging from 1 to 0, where 1 is equal to normal mobility, that is, no decrease in the population's mobility and would correspond to a value of 0 in the scale of the input variable (DATA overall mobility fractional decrease variable). 0 would here represent a mobility of 0 (-100 mobility in the input). For this transformation, we add 100 to the input variable to convert it from 0 to -100 to 0 to 100 and then divide by 100 to get a scale ranging from 1 to 0.
Behavioural_Model.grocery_and_pharmacy_fractional_change = GRAPH(TIME)
Points(101): (45,0, 1,0), (46,0, 3,0), (47,0, 0,0), (48,0, -1,0), (49,0, 4,0), (50,0, -2,0), ...
UNITS: dmnl
DOCUMENT: Data from COVID-19 Community Mobility Reports by Google. Described as being based on "aggregated, anonymized sets of data from users who have turned on the Location History setting, which is off by default"
Google (2020)
https://www.google.com/covid19/mobility/
Behavioural_Model.mobility_avg_IHME_time_of_survey = HISTORY(DATA_overall_mobility_IHME; average_time_of_survey)
UNITS: dmnl
DOCUMENT: The reduction in mobility according to data at the time of survey. The HISTORY function here gives the value of the input (DATA overall mobility) at the specified time (average time of survey).
Behavioural_Model.retail_and_recreation_fractional_change = GRAPH(TIME)
Points(101): (45,0, 7,0), (46,0, -5,0), (47,0, -5,0), (48,0, -5,0), (49,0, -1,0), (50,0, -9,0), ...
UNITS: dmnl

DOCUMENT: Data from COVID-19 Community Mobility Reports by Google. Described as being based on "aggregated, anonymized sets of data from users who have turned on the Location History setting, which is off by default" Google (2020)
Behavioural_Model.transit_stations_fractional_change = GRAPH(TIME)
Points(101): (45,0, 7,0), (46,0, -5,0), (47,0, -5,0), (48,0, -5,0), (49,0, -1,0), (50,0, -9,0), ...
UNITS: dmnl
DOCUMENT: Data from COVID-19 Community Mobility Reports by Google. Described as being based on "aggregated, anonymized sets of data from users who have turned on the Location History setting, which is off by default" Google (2020)
Behavioural_Model.workplaces_fractional_change = GRAPH(TIME)
Points(101): (45,0, -1,0), (46,0, -3,0), (47,0, -12,0), (48,0, -11,0), (49,0, -12,0), (50,0, -14,0), ...
UNITS: dmnl
DOCUMENT: Data from COVID-19 Community Mobility Reports by Google. Described as being based on "aggregated, anonymized sets of data from users who have turned on the Location History setting, which is off by default" Google (2020)
********** Behavioural_Model.Population:_Adoption_of_Hygienic_Behaviour: **********
Behavioural_Model.costs_due_to_fatigue_from_hygienic_behaviour = GRAPH(recent_intensity_of_adoption_of_hygienic_behaviour)
Points(11): (0,000, 0,0000), (0,100, 0,00427542373191), (0,200, 0,0108807954591), (0,300, 0,0210858507682), (0,400, 0,0368522842353), (0,500, 0,0612108415135), ...
UNITS: dmnl
DOCUMENT: Fatigue from engagement with hygienic behaviour is expected to produce some costs for the individual (they are expected to get tired or bored of engaging to the behaviour). This effect, for the case of hygienic behaviour is expected to be relatively "slow": the individual might be practicing the behaviour for some time and with a high intensity but continuing to do so is not expected to be equally costly.
Behavioural_Model.costs_due_to_fatigue_from_hygienic_behaviour_1 = GRAPH(recent_intensity_of_adoption_of_hygienic_behaviour)
Points(11): (0,000, 0,000), (0,100, 0,100), (0,200, 0,200), (0,300, 0,300), (0,400, 0,400), (0,500, 0,500), ...
UNITS: dmnl
DOCUMENT: Fatigue from engagement with hygienic behaviour is expected to produce some costs for the individual (they are expected to get tired or bored of engaging to the behaviour). This effect, for the case of hygienic behaviour is expected to be relatively "slow": the individual might be practicing the behaviour for some time and with a high intensity but continuing to do so is not expected to be equally costly.
Behavioural_Model.costs_due_to_fatigueness_from_social_distancing_1 = GRAPH(recent_intensity_of_adoption_of_hygienic_behaviour)

Points(11): (0,000, 0,0000), (0,100, 0,0193054347518), (0,200, 0,0442932083614), (0,300, 0,0766358537353), (0,400, 0,11849819514), (0,500, 0,172682248658), ...
UNITS: dmnl
Behavioural_Model.Difference_between_Protection_Motivation_and_Perceived_Costs_of_Hygienic_Behaviour = (Protection_Motivation-Perceived_Costs_of_Hygienic_behaviour_relative_to_reference_time)
UNITS: Dmnl
Behavioural_Model.Ease_of_engagement_in_hygienic_behavior = GRAPH(TIME)
Points: (0,0, 0,300), (45,0, 0,750), (55,0, 0,900), (130,0, 0,900) {GF DISCRETE}
UNITS: dmnl
DOCUMENT: This variable aims to describe how easy it is for an individual to engage in prophylactic behaviours (availability of sanitizers, masks, and even sanitation equipment in general). Over time, this easy is expected to increase due to governmental instructions or private business initiatives
Behavioural_Model.Ease_of_engagement_in_hygienic_behavior_Scenario_No1 = GRAPH(TIME)
Points(8): (0,0, 0,300), (45,0, 0,750), (55,0, 0,900), (130,0, 0,900), (155,0, 0,900), (200,0, 0,750), ... {GF DISCRETE}
UNITS: dmnl
DOCUMENT: This variable is adjusted to test the policy scenario No1. It represents an ease of engagement that returns close to the normal levels over time.
Behavioural_Model.level_of_adoption_of_hygienic_behaviour = GRAPH(Difference_between_Protection_Motivation_and_Perceived_Costs_of_Hygienic_Behaviour)
Points(11): (-1,000, 0,000), (-0,850, 0,0265969935769), (-0,700, 0,062973356057), (-0,550, 0,1418510649), (-0,400, 0,289050497375), (-0,250, 0,500), ...
UNITS: Dmnl
DOCUMENT: The difference between Protection Motivation and costs of hygienic behaviour is expected to have a non-linear effect on the adoption of such behaviour.
At the reference time, the relationship between the two considerations is 0, hence the point 0,1 allows us to achieve the reference mobility reduction at the reference time. When Costs are much higher that Motivation (with a maximum difference of -2), the population is expected to have regular mobility. When the Motivation is much higher than the costs (with the maximum difference being 2), the population is expected to reach the minimum mobility (1/2 of that observed at the reference period). The shape is attempting to capture a risk-aversion, as changes in the lower region (difference between Motivation and Costs lower than 0) lead to more steep responses than changes at the higher region (Motivation and Costs higher than 0)
Behavioural_Model.maximum_effect_of_hygiene_on_risk_reduction = ,13
UNITS: dmnl
DOCUMENT: The maximum possible risk reduction due to adoption of hygiene measures. It is hypothesised to be 13%.
Behavioural_Model.Perceived_Costs_of_HYGIENIC_BEHAVIOUR = (1-((weight_of_ease_of_engagement_with_hygienic_behaviour*Perceived_Ease_of_engagement_in_hygienic_

behavior) +(weight_of_social_costs_for_hygienic_behaviour*Social_Costs_of_hygienic_behaviour))) + weight_of_fatigue_from_hygienic_behaviour*costs_due_to_fatigue_from_hygienic_behaviour
UNITS: dmnl
DOCUMENT: The costs of prophylactic behaviour come from three sources, the perceived ease of engaging in this behaviour, a mechanism of Social Costs assosiated with practicing the behaviour (social norms based on the behaviour of others), and the costs due to fatigue from practicing the behaviour. Each of those mechanisms is multiplied by their associated weight to give its total contribution to the overall costs of hygienic behaviour.
Behavioural_Model.Perceived_costs_of_hygienic_behaviour_at_reference_time = ,41
UNITS: dmnl
DOCUMENT: The Perceived costs of hygienic behaviour at the reference time are estimated from running the behavioural model with data (partial model testing)
Behavioural_Model.Perceived_Costs_of_Hygienic_behaviour_relative_to_reference_time = Perceived_Costs_of_HYGIENIC_BEHAVIOUR/Perceived_costs_of_hygienic_behaviour_at_reference_time
UNITS: dmnl
Behavioural_Model.Perceived_Ease_of_engagement_in_hygienic_behavior = SMTH1(Ease_of_engagement_in_hygienic_behavior; time_to_perceive_changes_in_ease_of_other_hygienic_behaviour) {DELAY CONVERTER}
UNITS: dmnl
DOCUMENT: The perception of the livelihood costs follows a first order information delay with an delay time of 5 days.
Behavioural_Model.Perceived_Others_adoption_of_hygienic_behaviour = SMTH1(level_of_adoption_of_hygienic_behaviour; time_to_perceive_behaviour_of_others; 0) {DELAY CONVERTER}
UNITS: dmnl
DOCUMENT: The perceived by an average individual of how strongly others are engaging in prophylactic behaviours.
Behavioural_Model.recent_intensity_of_adoption_of_hygienic_behaviour = SMTH1(level_of_adoption_of_hygienic_behaviour; time_to_update_perception_of_recent_hygienic_behaviour_intensity; 0) {DELAY CONVERTER}
UNITS: dmnl
DOCUMENT: The level of adoption of hygienic behaviour is perceived as a first order smoothing to form a person perception of the recent intensity of adoption of such behaviour over the time to update their perception
Behavioural_Model.Social_Costs_of_hygienic_behaviour = Perceived_Others_adoption_of_hygienic_behaviour
UNITS: dmnl
DOCUMENT: The mechanism of Social Costs associated with the behaviour. It aims to capture costs of not complying with the "norm" around the individual and is assumed to be linear and equal to the Perceived adoption of hygienic behaviour of the population.

Behavioural_Model.time_to_perceive_changes_in_ease_of_other_hygienic_behaviour = 3
UNITS: days
DOCUMENT: The time to perceive changes in how easy it is for an individual to engage in hygienic behaviour. It is considered to be 3 days.
Behavioural_Model.time_to_update_perception_of_recent_hygienic_behaviour_intensity = 30
UNITS: days
DOCUMENT: The time to update one's perception about the intensity of adoption of the hygienic behaviour. It is assumed to be one month
Behavioural_Model.total_effect_of_hygienic_behaviour_on_risk_reduction = maximum_effect_of_hygiene_on_risk_reduction*level_of_adoption_of_hygienic_behaviour
UNITS: dmnl
DOCUMENT: The total effect of Hygienic Behaviour on the reduction of the risk for a "hot contact" is given as the product of the level of adoption of the hygienic behaviour of the population and the hypothesised maximum effect of hygienic behaviour on risk reduction.
Behavioural_Model.weight_of_ease_of_engagement_with_hygienic_behaviour = ,6
UNITS: dmnl
DOCUMENT: The weight, or relative significance of the ease of engagement with hygienic behaviour on the total perception of costs of hygienic behaviour for an average individual. The weight is assumed to be 60% reflecting that, if an individual does not have easy access to hygienic measures, this will have a high significance in their evaluation of the costs of such measures
Behavioural_Model.weight_of_fatigue_from_hygienic_behaviour = (1-weight_of_ease_of_engagement_with_hygienic_behaviour)*relative_weight_of_fatigue
UNITS: dmnl
DOCUMENT: The total weight of fatigue is given as the difference of the total weight of all costs (1) and the weight of ease of engagement with hygienic behaviour, multiplied by the relative weight of fatigue.
Behavioural_Model.weight_of_social_costs_for_hygienic_behaviour = (1-weight_of_ease_of_engagement_with_hygienic_behaviour)*(1-relative_weight_of_fatigue)
UNITS: dmnl
DOCUMENT: The weight of social costs is equal to whatever of the total weight remains after the weight weight of ease of engagement with hygienic behaviour and the weight of fatigue have been taken away.
********** Behavioural_Model.Population:_Efficacy_Appraisal: **********
Behavioural_Model.Efficacy_Appraisal(t) = Efficacy_Appraisal(t - dt) + (rate_of_increase_of_Efficacy - fading_rate_of_Efficacy) * dt
INIT Behavioural_Model.Efficacy_Appraisal = 0
UNITS: dmnl
DOCUMENT: The subjective perception of how efficient the proposed response is to mitigate the Threat posed by COVID-19. It has been desribed as the evaluation of ‘‘...the effectiveness, feasibility, and ease with

which a recommended response impedes or averts a threat.'' (Witte, Cameron, McKeon, & Berkowitz, 1996, p. 320). It is represented as a stock as it is expected to have some "memory", and it increases through the rate of increase and decreases through the fading rate. The range of this stock is in "absolute terms": an Efficacy Appraisal equal to 1 is the maximum Efficacy Appraisal than we can observe, and one equal to 0 is the minimum (response is perceived as having no Efficacy whatsoever)
INFLOWS:
Behavioural_Model.rate_of_increase_of_Efficacy = (Indicated_Efficacy_Appraisal-Efficacy_Appraisal)/time_to_update_Efficacy_Appraisal
UNITS: Per Day
DOCUMENT: The rate at which the Efficacy Appraisal increases. It is described as a goal/gap formulation where the Indicated Efficacy Appraisal as its explicit goal and the adjustment to this goal happening over the time to update the Efficacy Appraisal
OUTFLOWS:
Behavioural_Model.fading_rate_of_Efficacy = (Efficacy_Appraisal/time_to_discount_Efficacy_Appraisal)
UNITS: Per Day
DOCUMENT: The Efficacy Appraisal fades, or gets discounted over some time equal to the time to discount Efficacy Appraisal.
Behavioural_Model.Efficacy_Appraisal_relative_to_to_reference_time = (Efficacy_Appraisal/average_Efficacy_Apprasail_reference_time)*1
UNITS: dmnl
DOCUMENT: The, relative to the reference time, value of the Efficacy Appraisal. It is given as the ratio of the level of Efficacy Appraisal and the value of the Efficacy Appraisal at the reference time
Behavioural_Model.Indicated_Efficacy_Appraisal = MIN(1; (Total_Bottom_Up_communication_Contribution_to_Efficacy_Appraisal+Total_Observations_Contribution_to_Efficacy_Appraisal+Total_Top_Down_Contribution_to_Efficacy_Appraisal))
UNITS: dmnl
DOCUMENT: The indicated, by the contributions of the Efficacy-Related mechanism, value for the Efficacy Appraisal. It is given as the sum of the weighted contributions of the Bottom Up, Top Down, and Observation mechanisms and their contributions to the Efficacy Appraisal.
Behavioural_Model.time_to_discount_Efficacy_Appraisal = 21*2
UNITS: days
DOCUMENT: The time over which the Efficacy Appraisal fades. It is considered to be a constant and equal to 42 days. The value is here higher than in the Threat Appraisal fading mechanism as Efficacy is expected to not get discounted equally fast as the Threat.
Behavioural_Model.time_to_update_Efficacy_Appraisal = 3
UNITS: day
DOCUMENT: The time for a person to update their Threat Assessment. This is considered to be a rather fast process of 1 day

********** Behavioural_Model.Population:_Efficacy_Appraisal_Due_to_Observations: **********
Behavioural_Model.expected_average_prophylactic_response_of_the_population = GRAPH(perceived_average_prophylactic_response_of_the_population)
Points(11): (0,2000, 0,2000), (0,2800, 0,229617697545), (0,3600, 0,265397089097), (0,4400, 0,308620059346), (0,5200, 0,360835177496), (0,6000, 0,42391317856), ...
UNITS: dmnl
DOCUMENT: The perceived average prophylactic response of the population is perceived as being translated to somewhat more optimistic expectations in one's evaluations of how effective the response might be due to how intensively people are practicing it. Our assumption is that the Norwegian population in general tends to follow governmental advice and this is known amongst individuals (people expect that others will comply to a larger extent that we would perhaps observe in other countries).
Behavioural_Model.perceived_average_prophylactic_response_of_the_population = SMTH1((mobility_reduction-total_effect_of_hygienic_behaviour_on_risk_reduction); time_to_perceive_avg_prophylactic_response_of_the_population; 1) {DELAY CONVERTER}
INIT Behavioural_Model.perceived_average_prophylactic_response_of_the_population = 1
UNITS: dmnl
DOCUMENT: The perceived average prophylactic response of the population is based on observations regarding the extend to which the population is practing them. It is expected to be a first order smoothing process over some time to perceive this response. It is important to note that this is a "perfect information" mechanism: our assumption is that an average person observes the average intensity of prophylactic response at the population.
Behavioural_Model.reference_response_reference_time = (reference_mobility_reduction_at_reference_time--maximum_effect_of_hygiene_on_risk_reduction) + 0*(1-,385)
UNITS: dmnl
DOCUMENT: The perceived average prophylactic response of the population at the reference time
Behavioural_Model.time_to_perceive_avg_prophylactic_response_of_the_population = 7
UNITS: days
DOCUMENT: The time to perceive the average prophylactic response of the population. It is assumed to be equal to one week. This might be a low value but aims to capture the high alertness around COVID-19.
Behavioural_Model.Total_Observations_Contribution_to_Efficacy_Appraisal = cases_contribution_EFFICACY_reference_time*((1-expected_average_prophylactic_response_of_the_population)/reference_response_reference_time)
UNITS: dmnl
DOCUMENT: The total contribution of observations on the Efficacy Appraisal describes how people's observations regarding how intensely the population follows the proposed measures impact their beliefs that the response can efficiently mitigate the environmental threat. While this is perhaps a simplified picture of how

people evaluate Efficacy based on observations, looking at the average adoption of prophylactic behaviour in the population might not be unreasonable for the case of COVID-19 where the actual efficacy does depend on the level of their adoption by the population
********** Behavioural_Model.Population:_Efficacy_Communication: **********
Behavioural_Model.BU_Efficacy_Related_communication_due_to_own_Efficacy_Appraisal = intensity_of_Efficacy_Related_communication_Bottom_Up* SMTH1(Efficacy_Appraisal_relative_to_to_reference_time; time_to_communicate_own_Appraisals; 0) {DELAY CONVERTER}
INIT Behavioural_Model.BU_Efficacy_Related_communication_due_to_own_Efficacy_Appraisal = 0
UNITS: dmnl
DOCUMENT: Represents the intensity of Efficacy Related communication due a person's own appraisal of the Efficacy of the proposed responses against Covid-19. This is expected to be smoothed over the time to communicate own appraisals. The intensity of the Bottom Up Efficacy-Related communication acts as a multiplier to explore whether a decision to amplify one's own Efficacy Appraisal in their communication with others might have an impact.
Behavioural_Model.Contribution_of_own_Efficacy_Appraisal_on_BU_Efficacy_Related_message = (1-fraction_of_TopDown_Efficacy_Related_message_replicated_in_BottomUp_Communications)*BU_Efficacy_Related_communication_due_to_own_Efficacy_Appraisal
UNITS: dmnl
DOCUMENT: The contribution of own Efficacy Appraisals on the communication message individuals share through the bottom-up mechanism (person-to-person communication). This mechanism represents the diffusion amongst the population of personal cognitions regarding the virus. It is the product of the, relative to the reference time, Bottom Up Efficacy Related communication due to a person's own Efficacy Appraisal and the inverse of the fraction in which Bottom Up communications replicate the Top Down distrubuted Efficacy Related communication.
Behavioural_Model.Contribution_of_TD_msg_on_BU_Efficacy_Related_communication = "Perceived_Top-Down_Efficacy_Related_communication_Message"*fraction_of_TopDown_Efficacy_Related_message_replicated_in_BottomUp_Communications
UNITS: dmnl
DOCUMENT: The total contribution of the Top Down message on the Bottom Up Efficacy Related Communications is given as the product of the intensity of the Perceived Top-Down Efficacy-Related message and the fraction of this message that is expected to be replicated in person-to-person communications (Bottom-Up mechanism)
Behavioural_Model.fraction_of_TopDown_Efficacy_Related_message_replicated_in_BottomUp_Communications = ,5
UNITS: dmnl

DOCUMENT: The message by the government is considered to be modified by a likelihood that individuals will follow & replicate in their own communications this message. The assumption here is that 50% of the intensity of the message by the government will be translated to intensity of the bottom-up message.
Behavioural_Model.intensity_of_Efficacy_Related_communication_Bottom_Up = 1
UNITS: dmnl
DOCUMENT: The intensity of Efficacy-Related communication is a parameter to facilitate testing of different policies. In the case of Efficacy communication, our baseline assumption is that individuals communicate their Efficacy Appraisal as is, without amplification
Behavioural_Model."Perceived_Top-Down_Efficacy_Related_communication_Message" = SMTH1("Actual_SharedTotal_Top-Down_Efficacy_Related_communication_message"; time_to_perceive_Top_Down_message; 0) {IF TOP_DOWN_EFFICACY_COMMUNICATION_2> 0 THEN SMTH1(TOP_DOWN_EFFICACY_COMMUNICATION_2; time_to_perceive_top_down_message; 0) ELSE 0} {DELAY CONVERTER}
INIT Behavioural_Model."Perceived_Top-Down_Efficacy_Related_communication_Message" = 0
UNITS: dmnl
Behavioural_Model.Total_Bottom_Up_communication_Contribution_to_Efficacy_Appraisal = BU_msg_contribution_efficacy_reference_time*Total_Bottom_Up_Efficacy_Related_communication_message
UNITS: dmnl
DOCUMENT: The actual contribution of the Bottom Up Efficacy-Related message is given as the the product of the distributed message (in relative terms) and the value of the contribution in the overall Efficacy Appraisal
Behavioural_Model.Total_Bottom_Up_Efficacy_Related_communication_message = MIN((Contribution_of_TD_msg_on_BU_Efficacy_Related_communication+Contribution_of_own_Efficacy_Appraisal_on_BU_Efficacy_Related_message)*relative_to_time_of_survey_rate_of_interaction_with_shared_information; max_multiplier_Efficacy_Related_Assessments)
UNITS: dmnl
DOCUMENT: The total, relative to the reference time, intensity of the Efficacy Related communication message that is distributed via the Bottom-Up mechanism is given as the sum of the contributions of the Top Down message as it is replicated amongst people and that of their distributed own Efficacy-Related cognitions. This intensity is multiplied by the, relative to the reference time, rate of interaction with shared information to give the actual value of the shared Efficacy-Related Information. To ensure that this value remains within appropriate limits, a MIN function is employed.
Behavioural_Model.Total_Top_Down_Contribution_to_Efficacy_Appraisal = "Perceived_Top-Down_Efficacy_Related_communication_Message"*TD_msg_Total_contribution_EFFICACY_reference_time
UNITS: dmnl

DOCUMENT: The total contribution of the Top Down message to the Efficacy Appraisal is given as the product of the Top Down Efficacy-Related communication message as it is perceived by the population and the relative contribution of such a message for assessments regarding the Efficacy of the proposed responses
********** Behavioural_Model."Population:_Mobility_Reduction_/_Social_Isolation": **********
Behavioural_Model.costs_due_to_fatigue_from_social_isolation = GRAPH(recent_isolation_intensity)
Points(11): (0,000, 0,0000), (0,100, 0,0489656196481), (0,200, 0,103080998469), (0,300, 0,162887741362), (0,400, 0,228984414312), (0,500, 0,302032535039), ...
UNITS: dmnl
DOCUMENT: Fatigue from social isolation can represent a serious cost for an individual (they are expected to miss being out, get tired, or bored of staying home). The effect of the recent isolation intensity on the costs of fatigue is not expected to be exactly linear: people can "withstand" some fatigue without it being very equally costly
Behavioural_Model.costs_due_to_fatigue_from_social_isolation_1 = GRAPH(recent_isolation_intensity)
Points(11): (0,000, 0,000), (0,100, 0,100), (0,200, 0,200), (0,300, 0,300), (0,400, 0,400), (0,500, 0,500), ...
UNITS: dmnl
DOCUMENT: Fatigue from social isolation can represent a serious cost for an individual (they are expected to miss being out, get tired, or bored of staying home). The effect of the recent isolation intensity on the costs of fatigue is not expected to be exactly linear: people can "withstand" some fatigue without it being very equally costly
Behavioural_Model.costs_due_to_fatigue_from_social_isolation_reference_time = ,075
UNITS: dmnl
DOCUMENT: The costs due to fatigue from social isolation at the reference time.This is the model-produced value from running the model with exogenous data (DATA ON SWITCH =1)
Behavioural_Model.Difference_between_Protection_Motivation_and_Perceived_Costs_of_Social_Isolation = Protection_Motivation-Perceived_Costs_of_Social_Isolation_relative_to_reference_time
UNITS: dmnl
Behavioural_Model.effect_of_the_difference_between_Protection_Motivation_&_Costs_on_mobility_reduction = GRAPH(Difference_between_Protection_Motivation_and_Perceived_Costs_of_Social_Isolation)
Points(13): (-2,000, 2,23828751088), (-1,66666666667, 2,176), (-1,33333333333, 2,017), (-1,000, 1,794), (-0,666666666667, 1,515), (-0,333333333333, 1,217), ...
UNITS: dmnl
DOCUMENT: The difference between Protection Motivation and costs of social isolation is expected to have a non-linear effect on mobility reduction. At the reference time, the relationship between the two considerations is 0, hence the point 0,1 allows us to achieve the reference mobility reduction at the reference time. When Costs are much higher that Motivation (with a maximum difference of -2), the population is expected to have regular mobility. When the Motivation is much higher than the costs (with the maximum

difference being 2), the population is expected to reach the minimum mobility (1/2 of that observed at the reference period). The shape is attempting to capture a risk-aversion, as changes in the lower region (difference between Motivation and Costs lower than 0) lead to more steep responses than changes at the higher region (Motivation and Costs higher than 0)
Behavioural_Model.Livelihood_Costs = GRAPH(TIME)
Points: (0,0, 0,793), (55,0, 0,624), (66,0, 0,300), (130,0, 0,400), (155,0, 0,500) {GF DISCRETE}
UNITS: dmnl
DOCUMENT: Costs associated with the individual's livelihood are considered here. These costs might be loss of job and income, lack of financial support, unavailability of online or any other solutions that allow the individual to stay at home etc. Governments and other institutions are crucial in reducing those costs for the individuals. The steps that are tested here are related to decisions by the Norwegian Government.
Behavioural_Model.livelihood_costs_reference_time = ,3
UNITS: dmnl
DOCUMENT: The livelihood costs at the reference time. Based on the assumptions used in this model (Livelihood Costs Variable).
Behavioural_Model.Livelihood_Costs_Scenario_No1 = GRAPH(TIME)
Points(8): (0,0, 0,795), (55,0, 0,624), (66,0, 0,300), (130,0, 0,400), (155,0, 0,500), (200,0, 0,650), ... {GF DISCRETE}
UNITS: dmnl
DOCUMENT: This variable is adjusted to test the policy scenario No1. It represents livelihood costs that return close to the normal levels over time.
Behavioural_Model.mobility_reduction = effect_of_the_difference_between_Protection_Motivation_&_Costs_on_mobility_reduction*reference_mobility_reduction_at_reference_time
UNITS: dmnl
DOCUMENT: The reduction in mobility for an average individual as a response to COVID-19. It is the product of the effect of the difference between Protection Motivation & Costs on mobility reduction (given in relative terms) & the reference mobility reduction for the reference period
Behavioural_Model.Perceived_Costs_of_SOCIAL_ISOLATION = (Social_Costs_of_isolation*weight_of_social_costs_for_mobility) + (Perceived_Livelihood_Costs*weight_of_livelihood_costs) + (costs_due_to_fatigue_from_social_isolation*weight_of_fatigue_from_distancing)
UNITS: dmnl
DOCUMENT: The Costs associated with practicing Social Isolation. The costs are assumed to be the weighted average of three mechanisms: Livelihood Costs, Social Costs, and Costs due to fatigue from Recent Social Isolation. Each of these factors is multiplied with the relevant weight (or relative significance) to give their total contribution on the costs of Social Isolation.
Behavioural_Model.Perceived_Costs_of_Social_Isolation_relative_to_reference_time = Perceived_Costs_of_SOCIAL_ISOLATION/Perceived_Costs_of_Social_Isolation_time_of_survey

UNITS: dmnl
Behavioural_Model.Perceived_Costs_of_Social_Isolation_time_of_survey = (Social_Costs_reference_time*weight_of_social_costs_for_mobility) + (livelihood_costs_reference_time*weight_of_livelihood_costs) + (costs_due_to_fatigue_from_social_isolation_reference_time*weight_of_fatigue_from_distancing)
UNITS: dmnl
Behavioural_Model.Perceived_Livelihood_Costs = SMTH1(Livelihood_Costs; time_to_perceive_changes_in_livelihood_costs) {DELAY CONVERTER}
UNITS: dmnl
DOCUMENT: The livelihood costs that relate to social isolation are here perceived by the population following a first order information delay.
Behavioural_Model.Perceived_Mobility_of_Population = SMTH1(mobility_reduction; time_to_perceive_behaviour_of_others; 1) {DELAY CONVERTER}
UNITS: dmnl
DOCUMENT: The perceived by an average individual mobility of the rest of the population.
Behavioural_Model.recent_isolation_intensity = SMTH1((1-mobility_reduction); time_to_update_perception_of_recent_distancing_intensity; 0) {DELAY CONVERTER}
UNITS: dmnl
DOCUMENT: Social Isolation, represented by the level of mobility reduction, is perceived as a first order smoothing to form a person perception of the intensity of recent distancing over the time to update this perception. The smoothing takes as an input the inverse of the mobility reduction, representing the "strenght" of social isolation.
Behavioural_Model.reference_mobility_reduction_at_reference_time = ,445
UNITS: dmnl
DOCUMENT: Based on mobility data from the Institute for Health Metrics and Evaluation (IHME) (2020).
Behavioural_Model.relative_weight_of_fatigue = ,6
UNITS: dmnl
DOCUMENT: The relative weight, or significance of fatigue for evaluations of the costs of prophylactic behaviour. This weight represents the weight of fatigue after the weight of livelihood costs have been removed. 60% of the remaining weight is considered to be assigned to fatigue and the remaining 40% to social costs.
Behavioural_Model.Social_Costs_of_isolation = Perceived_Mobility_of_Population
UNITS: dmnl
DOCUMENT: The mechanism of Social Costs associated with the behaviour. It aims to capture costs of not complying with the "norm" around the individual and is assumed to be linear and equal to the Perceived Mobility of the population.
Behavioural_Model.Social_Costs_reference_time = ,6
UNITS: dmnl
DOCUMENT: The social costs at the reference time.This is the model-produced value from running the model with exogenous data (DATA ON SWITCH =1)

Behavioural_Model.time_to_perceive_behaviour_of_others = 7
UNITS: days
DOCUMENT: The average time to perceive the behaviour of others is assumed equal to 7 days
Behavioural_Model.time_to_perceive_changes_in_livelihood_costs = 3
UNITS: days
DOCUMENT: The time to perceive changes in livelihood costs. It is assumed to be rather fast for this case and equal to 3 days.
Behavioural_Model.time_to_update_perception_of_recent_distancing_intensity = 30
UNITS: days
DOCUMENT: The time to update one's perception about the intensity of social isolation. It is assumed to be one month
Behavioural_Model.weight_of_fatigue_from_distancing = (1-weight_of_livelihood_costs)*relative_weight_of_fatigue
UNITS: dmnl
DOCUMENT: The total weight of fatigue is given as the difference of the total weight of all costs (1) and the weight of livelihood costs, multiplied by the relative weight of fatigue.
Behavioural_Model.weight_of_livelihood_costs = ,55*0+,6
UNITS: dmnl
DOCUMENT: The weight, or relative significance of livelihood costs on the total perception of costs of social isolation for an average individual. Livelihood costs are assumed to have the highest importance and factors like "need to work" or "fear of loss of income" have been reported as significant reasons for non-compliance with quarantine instructions (DiGiovanni, Conley, Chiu, & Zaborski, 2004; Teh et al., 2012)
Behavioural_Model.weight_of_social_costs_for_mobility = (1-weight_of_livelihood_costs)*(1-relative_weight_of_fatigue)
UNITS: dmnl
DOCUMENT: The weight of social costs is equal to whatever of the total weight remains after the weight of livelihood costs and the weight of fatigue have been taken away.
********** Behavioural_Model.Population:_Protection_Motivation: **********
Behavioural_Model.effect_of_relative_Efficacy_levels_on_Protection_Motivation = GRAPH(Efficacy_Relative_to_Threat)
Points(11): (0,000, 0,000), (0,100, 0,027), (0,200, 0,0953494648991), (0,300, 0,182425523806), (0,400, 0,320821300825), (0,500, 0,500), ...
UNITS: dmnl
DOCUMENT: The effect of relative Efficacy on Protection Motivation aims to capture elements of the interaction between Threat and Efficacy Appraisal that have been described in the literature. Specifically, both Cognitive Appraisal Theory (Folkman, Lazarus, Dunkel-Schetter, DeLongis, & Gruen, 1986; Lazarus &

Folkman, 1984) and the Extended Parallel Process Model (Witte, 1992, 1994, 1995; Witte & Allen, 2000) describe maladaptive responses when Threat significantly outweighs Efficacy beliefs (termed emotion-focused coping or Fear control responses respectively). This relationship is expected to be non-linear and is here hypothesised to look as an S-shaped curve. This curve indicates that, if Efficacy is equal to Threat (Efficacy Relative to Threat = 1), then this effect will be equal to 1. If Efficacy is very low (Efficacy Relative to Threat << 1), this effect will take a very small value. In middle ranges, small increases in relative Efficacy lead to larger increases of this Effect.
Behavioural_Model.effect_of_Threat_and_Efficacy_Appraisals_on_Protection_Motivation = ((Threat_Appraisal_relative_to_reference_time*relative_contribution_of_Threat_Appraisal_on_Protection_Motivation) +(1-relative_contribution_of_Threat_Appraisal_on_Protection_Motivation)*Efficacy_Appraisal_relative_to_to_reference_time)
UNITS: dmnl
DOCUMENT: The effect of both Threat and Efficacy Appraisals on Protection Motivation is given as a weighted average of both appraisals (in relative terms) as also proposed by N. Weinstein (1993). The contribution of each Appraisal is controlled by the relative contribution of Threat Apprasail on Protection Motivation. The formulation ensures that the total contribution of both Appraisals is equal to 1 as Threat Appraisal is multiplied by its contribution and Efficacy Appraisal is multiplied by whatever remains (1-relative contribution of Threat).
Behavioural_Model.Efficacy_Relative_to_Threat = MIN(2; (Efficacy_Appraisal_relative_to_to_reference_time//Threat_Appraisal_relative_to_reference_time))
UNITS: dmnl
DOCUMENT: The relationship between Efficacy and Threat is given as the ratio of Efficacy relative to Threat. The ratio describes that, if Efficacy is very low and Threat very high, this variable will return a very low value, while if efficacy is higher than the Threat, the value will be higher than 1. In the case where Efficacy is equal to Threat, the variable will take a value of 1.
Behavioural_Model.Protection_Motivation = effect_of_Threat_and_Efficacy_Appraisals_on_Protection_Motivation*effect_of_relative_Efficacy_levels_on_Protection_Motivation
UNITS: dmnl
DOCUMENT: The motivation to act to mitigate an environmental Threat. The term Protection Motivation comes from the theory with the same name (Protection Motivation Theory (PMT), see Floyd, Prentice-Dunn, & Rogers, 2000; Maddux & Rogers, 1983; Rogers, 1975; Rogers & Mewborn, 1976) and is also used in the Extended Parallel Process Model (EPPM) (Witte, 1992, 1994, 1995; Witte & Allen, 2000). Protection Motivation is considered, in these approaches to come from the evaluations of Threat and Efficacy (effect of Threat and Efficacy Appraisals on Protection Motivation). The relationship between those two Appraisals is also significant according to these theories. For this, the effect of relative Efficacy levels on Protection Motivation acts as a multiplier. If any of those effects become 0, Protection Motivation is expected to be 0.
Behavioural_Model.relative_contribution_of_Threat_Appraisal_on_Protection_Motivation = ,6
UNITS: dmnl

********** Behavioural_Model.Population:_Susceptibility_Assessment: **********
Behavioural_Model.DATA_Reported_and_Perceived_New_Cases_per_10000_SUSC_Time_of_Survey = ,42
UNITS: People/ten thousand people/Day
Behavioural_Model.effect_of_relative_new_cases_on_Susceptibility_Assessment = GRAPH(Reported_and_Perceived_New_Cases_per_10000_Susceptible/DATA_Reported_and_Perceived_New_Cases_per_10000_SUSC_Time_of_Survey)
Points(13): (0,000, 0,000), (0,250, 0,303), (0,500, 0,582), (0,750, 0,814), (1,000, 1,000), (1,250, 1,157), ...
UNITS: dmnl
DOCUMENT: The effect of the, relative to the reference time, new cases on a person's Susceptibility Assessment. This effect ranges from 0 to 1,55. 0 indicates no risk perceived due to New Cases and 1,55 is the maximum value this effect can take to ensure that Susceptibility Assessment remain within reasonable bounds (see "max multiplier Threat-Related Assessments). The effect is expected to be non-linear and can be read as: If the new daily cases are 0, the risk is expected to be 0, while if the new cases are 3 times the threshold value, the risk is assumed to take its maximum value of 1. The shape of the effect indicates that small increases in the number of new cases when those are relative low elicit a larger increase in the perception of risk (1 additional new case if there were 2 cases the previous day makes people very **risk-responsive**). At higher values of new cases relative to the reference period value, the effect saturates: small changes do not increase the risk perception as much as in the "lower" region. The steepness of the "lower" region we believe is justified due to the already alerted population before and around the introduction of the virus to Norway as a result of the global situation in other countries.
Behavioural_Model.Susceptibility_Assessment = Total_Top_Down_Contribution_to_Susceptibility_Assessments+Total_Observations_Contribution_to_Susceptibility_Assessment+Total_Bottom_Up_communication_Contribution_to_Susceptibility_Assessment
UNITS: dmnl
DOCUMENT: The total Susceptibility Assessment represents how large an average individual perceives the risk to become infected with COVID-19 to be. The Susceptibility Assessment is conseptualised as the addition of the weighted contributions of the New Cases, Top-Down message, and Bottom-Up message on Susceptibility Assessments
Behavioural_Model.Total_Bottom_Up_communication_Contribution_to_Susceptibility_Assessment = MIN((BU_msg_contribution_Susceptibility_reference_time*max_multiplier_Threat_Related_Assessments); (BU_msg_contribution_Susceptibility_reference_time*Total_Bottom_Up_Threat_Related_communication_message))
UNITS: dmnl
DOCUMENT: The actual contribution of the Bottom Up Threat-Related message on the Susceptibility Assessment is given as the the product of the distributed message (in relative terms) and the value of the Top Down contribution in the overall Susceptibility Assessment

To ensure that this value remains within appropriate limits, a MIN function is employed.
Behavioural_Model.Total_Observations_Contribution_to_Susceptibility_Assessment = effect_of_relative_new_cases_on_Susceptibility_Assessment*cases_contribution_Susceptibility_reference_time
UNITS: dmnl
DOCUMENT: The final value of the contribution of observations on Susceptibility Assessment. The new reported cases are expected to be the main input on observations, in accordance with comparison between the development of cases and of susceptibility perceptions by Dohle (2020). The value of this contribution It is the product of the effect of new cases, given as relative to the reference time, and the value of the contribution of cases at the reference time
Behavioural_Model.Total_Top_Down_Contribution_to_Susceptibility_Assessments = MIN((TOP_DOWN_communication_Total_contribution_on_Susceptibility_at_reference_time*Perceived_Top_Down_Threat_Related_communication_Message); max_multiplier_Threat_Related_Assessments*TOP_DOWN_communication_Total_contribution_on_Susceptibility_at_reference_time)
UNITS: dmnl
DOCUMENT: The total contribution of the Top Down message to Susceptibility Assessments is given as the product of the Top Down Threat-Related communication message as it is perceived by the population and the relative contribution of such a message for assessments regarding one's Susceptibility to COVID-19 infection.
********** Behavioural_Model.Population:_Threat_Appraisal: **********
Behavioural_Model.Indicated_Threat_Appraisal = (weight_on_severity_for_threat_Appraisal*Total_Severity_Assessment) + (1-weight_on_severity_for_threat_Appraisal)*Susceptibility_Assessment
UNITS: dmnl
DOCUMENT: The indicated, by the contributions of the Threat-Related mechanisms, value for the Threat Appraisal. It is given as the sum of the weighted contributions of the Bottom Up, Top Down, and Observation mechanisms and their contributions to the Threat Appraisal.
Behavioural_Model.Threat_Appraisal(t) = Threat_Appraisal(t - dt) + (rate_of_increase_of_Threat - fading_rate_of_Threat) * dt
INIT Behavioural_Model.Threat_Appraisal = 0
UNITS: dmnl
DOCUMENT: The aggregated Threat Assessments of individuals in the population. Threat is sometimes distinguished between a cognitive and an emotional component however, here, we do not differentiate between the two. It represents a person's worry regarding the environmental health, their evaluation that there is

something that can be harmful to the person & lead to significant consequences. Threat is perceived as a "fading memory" mechanism declining over time based on the fading rate and building up through the rate of increase. The range of this stock is in "absolute terms": a Threat Appraisal equal to 1 is the maximum Threat Appraisal than we can observe, and one equal to 0 is the minimum (no Threat perceived)
INFLOWS:
Behavioural_Model.rate_of_increase_of_Threat = (Indicated_Threat_Appraisal-Threat_Appraisal)/time_to_update_Threat_Appraisal
UNITS: Per Day
DOCUMENT: The rate at which Threat Appraisal increases. It is described as a goal/gap formulation where the Indicated Threat Appraisal as its explicit goal and the adjustment to this goal happening over the time to update the Threat Appraisal
OUTFLOWS:
Behavioural_Model.fading_rate_of_Threat = (Threat_Appraisal/time_to_discount_Threat_Appraisal)
UNITS: Per Day
DOCUMENT: The Threat Appraisal fades, or gets discounted over some time equal to the time to discount Threat Appraisal.
Behavioural_Model.Threat_Appraisal_relative_to_reference_time = (Threat_Appraisal/average_Threat_Appraisal_reference_time)
UNITS: dmnl
DOCUMENT: The, relative to the reference time, value of the Threat Appraisal. It is given as the ratio of the level of Threat Appraisal and the value of the Threat Appraisal at the reference time
Behavioural_Model.time_to_discount_Threat_Appraisal = 31
UNITS: days
DOCUMENT: The time over which the Threat Appraisal fades. It is considered to be a constant and equal to 1 month
Behavioural_Model.time_to_update_Threat_Appraisal = 3
UNITS: day
DOCUMENT: The time for a person to update their Threat Assessment. This is considered to be a rather fast process of 1 day
********** Behavioural_Model."Population:_Threat-Related_Communication": **********
Behavioural_Model.BU_Threat_Related_communication_due_to_own_Threat_Appraisal = SMTH1(Threat_Appraisal_relative_to_reference_time; time_to_communicate_own_Appraisals; 0) {DELAY CONVERTER}
INIT Behavioural_Model.BU_Threat_Related_communication_due_to_own_Threat_Appraisal = 0
UNITS: dmnl

DOCUMENT: It represents the intensity of Threat Related communication due a person's own appraisal of the Threat posed by Covid-19. This is expected to be smoothed over the time to communicate own appraisals
Behavioural_Model.Contribution_of_own_Threat_Appraisal_on_BU_Threat_Related_message = (1-fraction_of_TopDown_Threat_Related_message_replicated_in_BottomUp_Communications)*BU_Threat_Related_communication_due_to_own_Threat_Appraisal
UNITS: dmnl
DOCUMENT: The contribution of own Threat Appraisals on the communication message individuals share through the bottom-up mechanism (person-to-person communication). This mechanism represents the diffusion amongst the population of personal cognitions regarding the virus. It is the product of the, relative to the reference time, Bottom Up Threat Related communication due to a person's own Threat Appraisal and the inverse of the fraction in which Bottom Up communications replicate the Top Down distrubuted Threat Related communication.
Behavioural_Model.Contribution_of_TD_msg_on_BU_Threat_Related_communication = Perceived_Top_Down_Threat_Related_communication_Message*fraction_of_TopDown_Threat_Related_message_replicated_in_BottomUp_Communications
UNITS: dmnl
DOCUMENT: The total contribution of the Top Down message on the Bottom Up Threat Related Communications is given as the product of the intensity of the Perceived Top-Down Threat-Related message and the fraction of this message that is expected to be replicated in person-to-person communications (Bottom-Up mechanism)
Behavioural_Model.fraction_of_TopDown_Threat_Related_message_replicated_in_BottomUp_Communications = ,5
UNITS: dmnl
DOCUMENT: The message by the government is considered to be modified by a likelihood that individuals will follow & replicate in their own communications this message. The assumption here is that 65% of the intensity of the message by the government will be translated to intensity of the bottom-up message.
Behavioural_Model.Perceived_Top_Down_Threat_Related_communication_Message = SMTH1(Total_Top_Down_Threat_Related_communication_message; time_to_perceive_Top_Down_message) {DELAY CONVERTER}
UNITS: Dmnl
DOCUMENT: The Total Top Down Threat Related communication is expected to be perceived by the population over some time equal to time to perceive Top Down message through a first order smoothing process (SMTH function). The value of this parameter is given relative to the reference time.
Behavioural_Model.time_to_communicate_own_Appraisals = 7
UNITS: Days
DOCUMENT: The average time for a person to communicate their own Appraisals with their network via the Bottom Up information dissemination mechanism. It is assumed to be equal to 7 days
Behavioural_Model.time_to_perceive_Top_Down_message = 2
UNITS: Days

DOCUMENT: The time for an average person to interact and perceive a top-down message is assumed to be 2 days. This is a rather short time period, however, we believe it is justified due to the high levels of alertness, especially at initial stages of the spread of the virus.
Behavioural_Model.Total_Bottom_Up_Threat_Related_communication_message = (Contribution_of_own_Threat_Appraisal_on_BU_Threat_Related_message + Contribution_of_TD_msg_on_BU_Threat_Related_communication)*relative_to_time_of_survey_rate_of_interaction_with_shared_information
UNITS: dmnl
DOCUMENT: The total, relative to the reference time, intensity of the Threat Related communication message that is distributed via the Bottom-Up mechanism is given as the sum of the contributions of the Top Down message as it is replicated amongst people and that of their distributed own Threat-Related cognitions. This intensity is multiplied by the, relative to the reference time, rate of interaction with shared information to give the actual value of the shared Threat-Related Information.
********** Behavioural_Model."Population;_Severity_Assessment": **********
Behavioural_Model.effect_of_relative_Severe_cases_on_Severity_Assessments = GRAPH(Perceved_Severe_Cases_relative_to_reference_time)
Points(13): (0,000, 0,000), (0,250, 0,303), (0,500, 0,582), (0,750, 0,814), (1,000, 1,000), (1,250, 1,157), ...
UNITS: dmnl
DOCUMENT: The effect on the Severity Assessments of the Perceived number of people that face severe consequences due to COVID-19 relative to the number of such cases at the reference period. The values and shape of the effect are the same as those described for the "effect of relative new cases on Susceptibility Assessments", as we expect those two evaluations to be rather similar.
Behavioural_Model.Perceived_Severe_Cases(t) = Perceived_Severe_Cases(t - dt) + (updating_rate_of_severe_cases - discounting_rate_of_severe_cases) * dt
INIT Behavioural_Model.Perceived_Severe_Cases = 0
UNITS: people
DOCUMENT: The Perception of how many people are facing severe consequences (death or hospitalization/intensive care) due to an infection. It is perceived to be a stock as so to capture a memory mechanism (the news of a death for example, are not "forgotten" immediately), in accordance with Poletti et al. (2011b). The stock increases through the updating rate and decreases through the discounting rate
INFLOWS:
Behavioural_Model.updating_rate_of_severe_cases = (Reported_and_Perceived_daily_deaths*weight_of_deaths) + (1-weight_of_deaths)*Reported_and_Perceived_New_Hospital_and_Intensive_Care_Admissions
UNITS: Person/Day

DOCUMENT: The increase in the perception of how many people are facing severe consequences due to the infection comes from the reported and perceived number of new deaths and hospitalizations/intensive care admissions. Those two elements are weighted by the value of the weight of death as it as assumed that they do not contribute equally to the perception of severe cases.
OUTFLOWS:
Behavioural_Model.discounting_rate_of_severe_cases = (Perceived_Severe_Cases/time_to_discount_a_severe_case)
UNITS: Person/Day
DOCUMENT: The forgetting (or discounting) rate for the Perception of People facing Severe Consequences.
Behavioural_Model.Perceved_Severe_Cases_relative_to_reference_time = (Perceived_Severe_Cases/PPeople_facing_severe_conseq_reference_period_from_DATA_1)
UNITS: dmnl
Behavioural_Model.PPeople_facing_severe_conseq_reference_period_from_DATA_1 = 63,8*0 + 59,1
UNITS: people
Behavioural_Model.Reported_and_Perceived_daily_deaths = DATA_ON_SWITCH* (SMTH3(Main_Infection_Model.New_Deaths_DATA; time_to_report_&_perceive_deaths_&_hospitalisations)) + (1-DATA_ON_SWITCH)* (SMTH3(Main_Infection_Model.Total_Dying_Tested*GOV_DECISION_Degree_of_presenting_virus_prevalence_&_severity_info; time_to_report_&_perceive_deaths_&_hospitalisations)) {DELAY CONVERTER}
UNITS: People/day
DOCUMENT: The number of daily new deaths that is reported by the authorities and perceived by an average individual. We perceive this to be best represented by a third order information delay as there are distinct processes in place - a process by which the hospital reports a death, the government reports the death, and the people receive and perceive this information.
Behavioural_Model.Reported_and_Perceived_New_Hospital_and_Intensive_Care_Admissions = DATA_ON_SWITCH* (SMTH3(Main_Infection_Model.New_Hospital_Admissions_DATA+Main_Infection_Model.New_Intensive_Care_Admissions_DATA; time_to_report_&_perceive_deaths_&_hospitalisations)) + (1-DATA_ON_SWITCH)* (SMTH3((Main_Infection_Model.Becoming_Tested_Hospitalised+Main_Infection_Model.Becoming_Tested_CCI)*GOV_DECISION_Degree_of_presenting_virus_prevalence_&_severity_info; time_to_report_&_perceive_deaths_&_hospitalisations)) {ok, the decision rule is not considered in the data option - we know for a fact that this is what they have reported} {DELAY CONVERTER}
UNITS: People/Day
DOCUMENT: The number of daily new hospitalisations and critical care admissions that is reported by the authorities and perceived by an average individual. We take as an input the hospitalisations & admissions that have been identified or get identified while hospitalised through testing. We assume both factors to contribute equally and we perceive the process to be best represented by a third order information delay due to the

existence of distinct processes in place - reporting by the hospital, reporting by the government, and peoples' receiving and perceiving of this information.
Behavioural_Model.time_to_discount_a_severe_case = 7
UNITS: days
Behavioural_Model.time_to_report_&_perceive_deaths_&_hospitalisations = 3
UNITS: days
DOCUMENT: The time to perceive a new death or hospital/intensive care admission. The value might be considered quite low but it aims to represent a high responsive by both the authorities and the population, as we believe has been the case with COVID-19. The value has been estimated to account for 1-1,5 days where the hospital offers and the government receives and publishes the information (through daily reports accounting for all information received until 8:00 each day), and 1-1,5 days for the public to receive and perceive the new information.
Behavioural_Model.Total_Bottom_Up_communication_Contribution_to_Severity_Assessment = MIN(BU_msg_contribution_Severity_Assessment_reference_time*max_multiplier_Threat_Related_Assessments; (BU_msg_contribution_Severity_Assessment_reference_time*Total_Bottom_Up_Threat_Related_communication_message))
UNITS: dmnl
DOCUMENT: The actual contribution of the Bottom Up Threat-Related message on the Severity Assessment is given as the the product of the distributed message (in relative terms) and the value of the Top Down contribution in the overall Severity Assessment
Behavioural_Model.Total_Observations_Contribution_to_Severity_Assessment = effect_of_relative_Severe_cases_on_Severity_Assessments*cases_contribution_Severity_reference_time
UNITS: dmnl
DOCUMENT: The final value of the contribution of observations on Severity Assessment. The Perceived Severe cases expected to be the main input on observations The value of this contribution It is the product of the effect of severe cases cases, given as relative to the reference time, and the value of the contribution of cases at the reference time
Behavioural_Model.Total_Severity_Assessment = Total_Top_Down_Contribution_to_Severity_Assessments+Total_Bottom_Up_communication_Contribution_to_Severity_Assessment+Total_Observations_Contribution_to_Severity_Assessment
UNITS: dmnl
DOCUMENT: The total Severity Assessment represents how severe an average individual perceives the consequences of becoming infected with COVID-19 to be. The Severity Assessment is conseptualised as the addition of the weighted contributions of the Severe Cases, Top-Down message, and Bottom-Up message on Severity Assessments
Behavioural_Model.Total_Top_Down_Contribution_to_Severity_Assessments = MIN(max_multiplier_Threat_Related_Assessments*TOP_DOWN_communication_Total_contribution_on_Severity_at_reference_time;

(Perceived_Top_Down_Threat_Related_communication_Message*TOP_DOWN_communication_Total_contribution_on_Severity_at_reference_time))
UNITS: dmnl
DOCUMENT: The total contribution of the Top Down message to Severity Assessments is given as the product of the Top Down Threat-Related communication message as it is perceived by the population and the relative contribution that such a message has for assessments regarding one's perceived consequences of a COVID-19 infection.
Behavioural_Model.weight_of_deaths = ,70
UNITS: dmnl
DOCUMENT: The weight people place on the number of people dying relative to the number of people being hospitalised or admitted to critical care when evaluating how many people are facing severe consequences due to an infection by COVID-19. A death is perceived to have a higher significance in this severity evaluation and we therefore chose a value of 70% with a corresponding weight of 30% for hospitalisations.
********** Behavioural_Model.Reported_Perceptions_Survey_DATA: **********
Behavioural_Model.avg_reported_following_of_advice_reference = 4,655487053/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "I do my best to follow the various advice from health authorities to limit the risk of infection (wash hands frequently, avoiding travel and social situations, keeping distance and avoiding touching surfaces)"
Behavioural_Model.avg_reported_information_gathering_from_health_authorities_reference = 3,724022346/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "I pay attention to advice from the health authorities". In norwegian, the verb "følger med" is used that tends to denote an active attention .....
Behavioural_Model.avg_reported_risk_reduction_OTHERS_by_following_advice_reference = 4,430932412/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and

29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "By following the infection prevention advice, I will avoid making others sick"
Behavioural_Model.avg_reported_risk_reduction_SELF_by_following_advice_reference = 4,045140602/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "By following the infection prevention advice, I will avoid getting sick"
Behavioural_Model.avg_reported_significance_of_source_credibility_reference = 4,180629001/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "It is important to me that information about the disease comes from a credible source"
Behavioural_Model.avg_reported_trust_in_health_authorities_reference = 4,184015787/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "To what extent do you trust the advice of the health authorities?"
Behavioural_Model.avg_risk_of_infection_OTHERS_reference = 3,434966426*0 + 3,434966426/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). This value represents participants' average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "How large do you consider the risk to be that in 2020... an average adult will be infected". The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020.
Behavioural_Model.avg_risk_of_infection_SELF_reference = 2,946148093*0 + 2,946148093/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The value here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "How high or low do you think the risk is that you will be infected by the coronavirus in 2020?" The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020.
Behavioural_Model.avg_risk_of_serious_changes_in_everyday_life_reference = 3,586258033/5

UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "How large do you consider the risk to be that during 2020... your everyday life will be much changed"
Behavioural_Model.avg_risk_of_serious_illness_reference = 2,156605641/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "How large do you consider the risk to be that in 2020... you will become seriously ill"
Behavioural_Model.avg_severity_of_consequences_of_infection_SELF_reference = 2,958508274/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The value here reflects participants' average agreement with the statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "It would be very serious for me if I got infected by the virus". The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020.
Behavioural_Model.avg_trust_that_info_is_presented_reference = 4,074882222/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: This is the reverted scale of answers to the question "Information about the coronavirus is deliberately concealed from us" such that a high value indicates the perception that information is not concealed.
Behavioural_Model.avg_worry_of_family_getting_infected_reference = 3,451316595/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and 29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "I worry someone in my family is going to be infected by the coronavirus"
Behavioural_Model.avg_worry_of_getting_infected_SELF_reference = 2,739065975/5
UNITS: dmnl
DOCUMENT: Based on data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The values reported here represent the weighted average of the perceptions of Norwegian citizens between 20 and

29 of March 2020. The value presented here represents average agreement with statement on a scale of 1 to 5 (1 being lowest and 5 highest agreement). The question item was: "I worry that I'm going to be infected by the coronavirus"
Behavioural_Model.TopDown_Threat_Communication_Assumed_from_Timeline = GRAPH(TIME)
Points(7): (35,0, 0,000), (42,0, 0,200), (51,0, 0,400), (66,0, 0,800), (90,0, 0,850), (122,0, 0,450), ... {GF DISCRETE}
UNITS: dmnl
DOCUMENT: Significant days under consideration (note that in our time label, February has 31 days. We follow this restriction & move March events 2 days earlier (e.g. 12.03 becomes 10.03, or, model time 74)): 11.02 - FHI publishes Facts about COVID (model time 42); 26.02 - FHI publishes a risk assessment specific for Norway (model time 51); 12.03 - Norway enters lock-down (model time 66); 07.05 - Norway announces gradual reopening (model time 122)
********** Behavioural_Model.Variable_Values_at_reference_time: **********
Behavioural_Model.average_time_of_survey = (80+81+82+83+84+85+86+87+88+89)/10 {between 20-29 March}
UNITS: day
DOCUMENT: Time of collection of the data reported by Sætrevik (2020) and collected by Ivarsflaten et al. (2020). The survey was performed between 20-29 March 2020 in the Norwegian Population. For clarity, we represent the model time corresponding to each of the data collection days and divide by the total number of days to find the average time.
Behavioural_Model.Costs_os_Social_Isolation_at_reference_time = HISTORY(Perceived_Costs_of_SOCIAL_ISOLATION; average_time_of_survey)
UNITS: dmnl
Behavioural_Model.Efficacy_Appraisal_at_reference_time = HISTORY(Efficacy_Appraisal; average_time_of_survey)
UNITS: dmnl
Behavioural_Model.reference_time_spike = IF TIME =average_time_of_survey THEN 1 ELSE 0
UNITS: day
Behavioural_Model.Severity_Assessment_at_reference_time = HISTORY(Total_Severity_Assessment; average_time_of_survey)
UNITS: dmnl
Behavioural_Model.Susceptibility_Assessment_at_reference_time = HISTORY(Susceptibility_Assessment; average_time_of_survey)
UNITS: dmnl
Behavioural_Model.Threat_Appraisal_at_reference_time = HISTORY(Threat_Appraisal; average_time_of_survey)

UNITS: dmnl
********** Behavioural_Model.Viral_Prevalence_Information: **********
Behavioural_Model.DATA_ON_SWITCH = 0
UNITS: dmnl
DOCUMENT: This Switch controls the input to the Susceptibility and Severity Assessments. When it is ON (1), the behavioural response structure takes as input the real-world data on the number of cases & hospitalisations. When it is OFF (0), the behavioural response structure takes input from the infection model.
Behavioural_Model.GOV_DECISION_Degree_of_presenting_virus_prevalence_&_severity_info = 1
UNITS: dmnl
Behavioural_Model.People_per_10000_people = 10000
UNITS: people/ten thousand people
DOCUMENT: The number of people per ten thousand people (10000).
Behavioural_Model.Reported_&_Perceived_New_Cases_2 = SMTH1(Reported_New_Cases_2*GOV_DECISION_Degree_of_presenting_virus_prevalence_&_severity_info; time_to_perceive_reported_cases) {DELAY CONVERTER}
UNITS: Person/Day
DOCUMENT: The number of new daily cases as they are perceived by an average individual, represented by a first order information delay with the reported new cases as its input.
Behavioural_Model.Reported_and_Perceived_New_Cases_per_10000_Susceptible = Reported_&_Perceived_New_Cases_2//Susc_10000_people_1
UNITS: People/ten thousand people/Day
DOCUMENT: The number of new cases per ten thousand susceptible people. It is the ratio of daily perceived cases to 10000 susceptible people.
Behavioural_Model.Reported_New_Cases_2 = (1-DATA_ON_SWITCH)* (SMTH3(Main_Infection_Model.Testing_rates_SUM; time_to_get_and_report_test_results)) + DATA_ON_SWITCH*(SMTH3(Main_Infection_Model.Confirmed_Daily_New_Cases_DATA; time_to_get_and_report_test_results)) {Could be a higher order} {ok, note that the decision rule is not considered in the data option - we know for a fact that this is what they have reported} {DELAY CONVERTER}
UNITS: Person/Day
DOCUMENT: The number of new daily cases that are confirmed via testing AND REPORTED BY THE GOVERNMENT. We take as an input the testing rate of infected across all severity categories. We perceive the process to be best represented by a third order information delay due to the existence of distinct processes in place - taking, processing and reporting the results of the actual test,
[[[[as well as the government reporting to the public the number of new confirmed cases]]]]]

Behavioural_Model.Susc_10000_people_1 = DATA_ON_SWITCH*("Data-Based_Susceptible"/People_per_10000_people) + (1-DATA_ON_SWITCH)*(Main_Infection_Model.Susceptible/People_per_10000_people)
UNITS: ten thousand people
DOCUMENT: The Susceptible population measured in ten thousand people.
Behavioural_Model.time_to_get_and_report_test_results = 3
UNITS: days
DOCUMENT: The time for a sample to be tested and reported. We estimate and average of TWO TO THREE days delay from specimen collection to confirmation based on discrepancies observed in the published data of the daily reports and those of the cases by specimen collection.
[[and one additional day of reporting new confirmed cases by the government in the daily reports]]
Behavioural_Model.time_to_perceive_reported_cases = 2
UNITS: days
DOCUMENT: The time it takes for an average person to access information and perceive a new case of COVID-19.The choice of TWO days might be considered quite fast but it aims to represent the high responsiveness to information by the media/GOVER?. and the public.
{ The model has 252 (252) variables (array expansion in parens).
In this module and 0 additional modules with 19 sectors.
Stocks: 8 (8) Flows: 11 (11) Converters: 233 (233)
Constants: 78 (78) Equations: 166 (166) Graphicals: 35 (35)
There are also 141 expanded macro variables.
}

Infectivity Module

********** Infectivity_Calc.Calculations: **********
Infectivity_Calc.Asym_NOT_Testted[Infection_Day] = Main_Infection_Model.AI_per_day_of_infection
UNITS: people
DOCUMENT: The Asymptomatic Infected population, arrayed per day of infection.
Infectivity_Calc.Hospitalised_NOT_Tested[Infection_Day] = Main_Infection_Model.HI_per_day_of_infection+Main_Infection_Model.CCI_per_day_of_infection
UNITS: People
DOCUMENT: The sum of the total (non-tested) Hospitalised and Critical Care Infected, arrayed per day of infection.

Infectivity_Calc.Symptomatic_NOT_Testted[Infection_Day] = Main_Infection_Model.SI_per_day_of_infection
UNITS: people
DOCUMENT: The Symptomatic Infected population, arrayed per day of infection.
Infectivity_Calc.TESTED_hospitalised[Infection_Day] = Main_Infection_Model.T_HI_per_day_of_infection+Main_Infection_Model.T_CCI_per_day_of_infection
UNITS: people
DOCUMENT: The sum of the total Tested Hospitalised and Critical Care Infected, arrayed per day of infection.
Infectivity_Calc.TESTED_outside_of_hospital[Infection_Day] = Main_Infection_Model.T_AI_per_day_of_infection+Main_Infection_Model.T_SI_per_day_of_infection
UNITS: people
DOCUMENT: The sum of the total Tested Asymptomatic and Symptomatic Infected, arrayed per day of infection.
********** Infectivity_Calc.Global_Contact_Rate_Sector: **********
Infectivity_Calc.baseline_contact_rate = 10
UNITS: Per Day
DOCUMENT: The baseline contact rate represents the average number of people one person contacts per day. The value used is of 10 people per person per day.
Infectivity_Calc.global_contact_rate = (1-PARTIAL_TESTING_INFECTION_MODEL_ON_SWITCH) *(baseline_contact_rate*Total_reduction_in_Global_Contact_rate_due_to_behavioural_measures) + PARTIAL_TESTING_INFECTION_MODEL_ON_SWITCH* (baseline_contact_rate*Total_reduction_in_Global_Contact_rate_due_to_behavioural_measures_DATA)
UNITS: Per Day
DOCUMENT: The global contact rate is equal to the product of the baseline contact rate assumed for the population and the total reduction in global contact rate due to behavioural measures. When the partial testing for the infection model is ON (=1), this variable uses the reduction in contacts from data. When it is off (=0), it uses the one coming from the behavioural model
Infectivity_Calc.PARTIAL_TESTING_INFECTION_MODEL_ON_SWITCH = 0
UNITS: dmnl
DOCUMENT: When this Switch is ON (=1), then the global contact rate is controlled by the data
Infectivity_Calc.risk_reduction_due_to_hygienic_behaviour_Assumption = GRAPH(TIME)
Points: (31,0, 0,0300), (50,0, 0,0600), (60,0, 0,1300), (155,0, 0,1044), (250,0, 0,1044) {GF DISCRETE}
UNITS: dmnl

Infectivity_Calc.Total_reduction_in_Global_Contact_rate_due_to_behavioural_measures = (Behavioural_Model.mobility_reduction-Behavioural_Model.total_effect_of_hygienic_behaviour_on_risk_reduction)
UNITS: dmnl
Infectivity_Calc.Total_reduction_in_Global_Contact_rate_due_to_behavioural_measures_DATA = (Behavioural_Model.DATA_overall_mobility_IHME-risk_reduction_due_to_hygienic_behaviour_Assumption)
UNITS: dmnl
********** Infectivity_Calc.Infected_Contacts_with_Susceptible: **********
Infectivity_Calc.contacts_Asymptomatic_not_tested[Infection_Day] = global_contact_rate*(Asym_NOT_Testted)
UNITS: Person/Day
DOCUMENT: The contacts of Asymptomatic, Not Tested, Infected as expected to be equal to those of the general population. Here, the global contact rate is multiplied by the number of Asymptomatic individuals (arrayed according to the day of infection they are at) to give us the total number of encounters per day that an average Asymptomatic Infected is expected to have.
Infectivity_Calc.contacts_between_Susceptible_and_infected_Asymptomatic[Infection_Day] = contacts_Asymptomatic_not_tested*fraction_of_population_susceptible
UNITS: Person/Day
DOCUMENT: The number of contacts that an Asymptomatic Infected has is here multiplied by the probability that a person they contact is Susceptible (as given by the fraction on population susceptible) to give the total number of contacts between a Susceptible person and an Asymptomatic Infected person, arrayed by the day of infection they are at.
Infectivity_Calc.contacts_between_Susceptible_and_infected_Hospitalised_Not_Tested[Infection_Day] = contacts_Hospitalised_not_tested*fraction_of_population_susceptible
UNITS: Person/Day
DOCUMENT: The number of contacts that an Infected Hospitalised (not-tested) has is here multiplied by the probability that a person they contact is Susceptible (as given by the fraction on population susceptible) to give the total number of contacts between a Susceptible person and an Infected Hospitalised person, arrayed by the day of infection they are at.
Infectivity_Calc.contacts_between_Susceptible_and_infected_Symptomatic_Not_Tested[Infection_Day] = contacts_Symptomatic_not_tested*fraction_of_population_susceptible
UNITS: Person/Day
DOCUMENT: The number of contacts that a Symptomatic Infected has is here multiplied by the probability that a person they contact is Susceptible (as given by the fraction on population susceptible) to give the total

number of contacts between a Susceptible person and a Symptomatic Infected person, arrayed by the day of infection they are at.
Infectivity_Calc.contacts_between_Susceptible_and_infected_Tested_Hospitalised[Infection_Day] = contacts_tested_in_hospital*fraction_of_population_susceptible
UNITS: Person/Day
DOCUMENT: The number of contacts that an Infected Tested and Hospitalised has is here multiplied by the probability that a person they contact is Susceptible (as given by the fraction on population susceptible) to give the total number of contacts between a Susceptible person and an Infected Tested and Hospitalised person, arrayed by the day of infection they are at.
Infectivity_Calc.contacts_between_Susceptible_and_infected_Tested_Out_of_Hospital[Infection_Day] = contacts_tested_out_of_hospital*fraction_of_population_susceptible
UNITS: Person/Day
DOCUMENT: The number of contacts that an Infected Tested and not Hospitalised has is here multiplied by the probability that a person they contact is Susceptible (as given by the fraction on population susceptible) to give the total number of contacts between a Susceptible person and an nfected Tested and not Hospitalised person, arrayed by the day of infection they are at.
Infectivity_Calc.contacts_Hospitalised_not_tested[Infection_Day] = Hospitalised_NOT_Tested*Hospitalised_contact_rate
UNITS: Person/Day
DOCUMENT: The contacts of the Hospitalised Infected are the product of the Severe contact rate and the number of Hospitalised Infected (arrayed according to the day of infection they are at) to give us the total number of encounters per day that an average Hospitalised Infected is expected to have.
Infectivity_Calc.contacts_Symptomatic_not_tested[Infection_Day] = Symptomatic_contact_rate*(Symptomatic_NOT_Testted)
UNITS: Person/Day
DOCUMENT: The contacts of the Symptomatic Infected are the product of the Symptomatic contact rate and the number of Symptomatic Infected (arrayed according to the day of infection they are at) to give us the total number of encounters per day that an average Symptomatic Infected is expected to have.
Infectivity_Calc.contacts_tested_in_hospital[Infection_Day] = TESTED_hospitalised*tested_contact_rate
UNITS: Person/Day
DOCUMENT: The contacts of Tested and Hospitalised Infected are the product of the tested contact rate and the number of Tested Hospitalised Infected (arrayed according to the day of infection they are at) to give us the total number of encounters per day that an average Tested Hospitalised Infected is expected to have.
Infectivity_Calc.contacts_tested_out_of_hospital[Infection_Day] = TESTED_outside_of_hospital*tested_contact_rate
UNITS: Person/Day
DOCUMENT: The contacts of Tested, non-Hospitalised Infected are the product of the tested contact rate and the number of Tested non-Hospitalised Infected (arrayed according to the day of infection they are at) to

give us the total number of encounters per day that an average Tested non-Hospitalised Infected is expected to have.
Infectivity_Calc.days_for_1_contact_Hospitalised = 1//Hospitalised_contact_rate[1]
UNITS: Day
DOCUMENT: The per day Contact rate for a Hospitalised Infected is converted here in days for 1 contact for an average Hospitalised Infected.
Infectivity_Calc.Days_for_1_contact_Symptomatic = 1//Symptomatic_contact_rate[1]
UNITS: Day
DOCUMENT: The per day Symptomatic Contact rate is converted here in days for 1 contact for an average Symptomatic Infected.
Infectivity_Calc.Days_for_1_contact_tested = 1//tested_contact_rate[1]
UNITS: Day
DOCUMENT: The per day Contact rate of a Tested Infected is converted here in days for 1 contact for an average Tested Infected.
Infectivity_Calc.fraction_of_population_susceptible = Main_Infection_Model.Susceptible/(Main_Infection_Model.NORWAY_INIT_POP-Main_Infection_Model.ALL_DEAD)
UNITS: dmnl
DOCUMENT: The fraction of the population that is Susceptible is given as the ration of the Susceptible stock to the Population of the country (the initial population minus the dead by the infection population). This calculation gives us the probability that a person is Susceptible.
Infectivity_Calc.Hospitalised_contact_rate[Infection_Day] = MIN(global_contact_rate; baseline_contact_rate * Hospitalised_fractional_contacts_adjustment)
UNITS: Per Day
DOCUMENT: The contact rate per Hospitalised Infected (Hospitalised and Critical Care) is given as the product of the baseline contact rate and fractional contacts adjustment for this population. A MIN function is used here so that, if the adjusted contact rate for the Hospitalised population is higher than the average contact rate for the entire population (the global contact rate), the Hospitalised contact rate will take the value of the global contact rate (since it is not reasonable that Hospitalised cases will have more contacts that the average population). This variable is arrayed so as to produce the contact rate of Hospitalised Infected for individuals at each day of infection. Structure initially developed by ISEE Systems (2020).
Infectivity_Calc.Hospitalised_fractional_contacts_adjustment = tested_fractional_contacts_adjustment
UNITS: dmnl
DOCUMENT: Individuals who are hospitalized (or in Critical Care) do not have many chances of coming in unprotected contact with individuals around them and are, moreover, expected to comply with quarantine protocols. The fractional adjustment of contacts for this category is assumed to be equal to that of tested infected (0,0145 accounting for 1 contact per 7 days)
Infectivity_Calc.Symptomatic_contact_rate[Infection_Day] = MIN(global_contact_rate; baseline_contact_rate * Symptomatic_fractional_contacts_adjustment)

UNITS: Per Day
DOCUMENT: The contact rate per Symptomatic Infected is given as the product of the baseline contact rate and fractional contacts adjustment for this population. A MIN function is used here so that, if the adjusted contact rate for the Symptomatic population is higher than the average contact rate for the entire population (the global contact rate), the Symptomatic contact rate will take the value of the global contact rate (since it is not reasonable that Symptomatic cases will have more contacts that the average population). This variable is arrayed so as to produce the contact rate of Symptomatic Infected for individuals at each day of infection. Structure initially developed by ISEE Systems (2020).
Infectivity_Calc.Symptomatic_fractional_contacts_adjustment = ,1*1
UNITS: Dmnl
DOCUMENT: Symptomatic Infected are assumed to reduce their contacts from the time they start experiencing symptoms & to generally comply with governmental instructions to "stay home" under suspicion of infection. We assume the adjustment to be equal to 10%, accounting for 1 contact daily.
Infectivity_Calc.tested_contact_rate[Infection_Day] = MIN(global_contact_rate; baseline_contact_rate * tested_fractional_contacts_adjustment)
UNITS: Per Day
DOCUMENT: The contact rate per Tested Infected is given as the product of the baseline contact rate and fractional contacts adjustment for this population. A MIN function is used here so that, if the adjusted contact rate for the Tested population is higher than the average contact rate for the entire population (the global contact rate), the Tested contact rate will take the value of the global contact rate (since it is not reasonable that Tested cases will have more contacts that the average population). This variable is arrayed so as to produce the contact rate of Tested Infected for individuals at each day of infection. Structure initially developed by ISEE Systems (2020).
Infectivity_Calc.tested_fractional_contacts_adjustment = 0,0145
UNITS: Dmnl
DOCUMENT: Individuals who are tested positive for COVID-19 are assumed to comply with self-isolation protocols. The fractional adjustment of contacts for this category is assumed to be 0,0145 accounting for 1 contact per 7 days
********** Infectivity_Calc.Infectivity_&_Infection_Rate: **********
Infectivity_Calc.infection_rate_Asymptomatic[Infection_Day] = contacts_between_Susceptible_and_infected_Asymptomatic* (infectivity_per_day_of_infection*relative_infectiousness_of_Asymptomatic)
UNITS: person/day
DOCUMENT: The infection rate from Infected Asymptomatic persons is the product of the contacts between Susceptible and Asymptomatic infected (arrayed per day of infection) and the infectivity per day of infection multiplied by the relative infectioussness of Asymptomatic Infected

Infectivity_Calc.infection_rate_Hospitalised_Not_Tested[Infection_Day] = contacts_between_Susceptible_and_infected_Hospitalised_Not_Tested*infectivity_per_day_of_infection
UNITS: person/day
DOCUMENT: The infection rate from Infected Hospitalised persons is the product of the contacts between Susceptible and infected Hospitalised Not Tested (arrayed per day of infection) and the infectivity per day of infection.
Infectivity_Calc.Infection_Rate_SUM = SUM(infection_rate_Hospitalised_Not_Tested) + SUM(infection_rate_Symptomatic_Not_Tested) + SUM(infection_rate_Asymptomatic) + SUM(infection_rate_Tested_Hospitalised) + SUM(infection_rate_Tested_Out_of_Hospital)
UNITS: person/day
DOCUMENT: The sum of the infection rates from all severity categories and across all days of infection
Infectivity_Calc.infection_rate_Symptomatic_Not_Tested[Infection_Day] = contacts_between_Susceptible_and_infected_Symptomatic_Not_Tested*infectivity_per_day_of_infection
UNITS: person/day
DOCUMENT: The infection rate from Infected Symptomatic persons is the product of the contacts between Susceptible and infected Symptomatic Not Tested (arrayed per day of infection) and the infectivity per day of infection.
Infectivity_Calc.infection_rate_Tested_Hospitalised[Infection_Day] = contacts_between_Susceptible_and_infected_Tested_Hospitalised*infectivity_per_day_of_infection
UNITS: person/day
DOCUMENT: The infection rate from Infected Hospitalised and Tested persons is the product of the contacts between Susceptible and infected Hospitalised Tested (arrayed per day of infection) and the infectivity per day of infection.
Infectivity_Calc.infection_rate_Tested_Out_of_Hospital[Infection_Day] = contacts_between_Susceptible_and_infected_Tested_Out_of_Hospital*infectivity_per_day_of_infection
UNITS: person/day
DOCUMENT: The infection rate from Infected Tested persons is the product of the contacts between Susceptible and infected Tested (arrayed per day of infection) and the infectivity per day of infection.
Infectivity_Calc.infectivity_per_day_of_infection[Infection_Day] = Normalised_relative_infectivity_per_day_of_infection*NORMAL_MAX_INFECTIVITY
UNITS: dmnl
DOCUMENT: The Infectivity arrayed per day of infection. The normalised relative infectivity is multiplied by the maximum infectivity to produce the value of the infectivity for each different day of infection. This mechanism produced the following result: if the arrayed element "Infection day" is equal to 1 (e.g. this parameter is multiplied with the contacts of an Infected person at their 1st day of infection), it will select the point x=1 from the distribution in the "Normalised relative infectivity per day of infection" variable. This point, which is normalised, will then by multiplied by the Normal Max Infectivity to produce the actual infectivity potential for a person according to the day of Infection they are.
Infectivity_Calc.NORMAL_MAX_INFECTIVITY = ,14

UNITS: dmnl
Infectivity_Calc.Normalised_relative_infectivity_per_day_of_infection[Infection_Day] = GRAPH(Transit_Day_TEST_INPUT)
Points(30): (0,00, 0,000), (0,62, 0,000), (0,78, 0,244), (1,04, 0,499), (1,20, 0,699), (1,27, 0,748), ...
UNITS: dmnl
DOCUMENT: The curve was estimated from the study by He et al. (2020; Figure 1c, middle) and was adjusted to account for the 2-day latency period that was included in the model and normalised on a scale from 0 to 1 to allow easy experimentation with the infectivity parameter. The Input "Transit Day" is only used in this case to allow the simulation to run and has no impact on the calculation.
Infectivity_Calc.relative_infectiousness_of_Asymptomatic = ,5*1 + ,7*0
UNITS: dmnl
DOCUMENT: The relative infectioussness of the Asymptomatic Infected describes the fraction of viral load or, more generally, infection potential that an asymptomatic person exhibits relative to all other severity categories. The model used by the Norwegian health authorities uses an estimate of 10% relative infectiousness of Asymptomatic (Norwegian Institute of Public Health - FHI, 2020a), but, here, we decided to use the more modest estimate of 50% used for the Imperial College model (Ferguson et al., 2020)
Infectivity_Calc.Transit_Day_TEST_INPUT[Infection_Day] = Infection_Day
UNITS: days
DOCUMENT: This is a variable used to allow the simulation to run. The variable has no input other than the Arrayed element itself, so that i returns 1 for the array "Infection day = 1", 2 for the the array "Infection day = 2"" etc.
{ The model has 56 (1552) variables (array expansion in parens).
In this module and 0 additional modules with 4 sectors.
Stocks: 0 (0) Flows: 0 (0) Converters: 56 (1552)
Constants: 6 (6) Equations: 50 (1546) Graphicals: 2 (46)
There are also 141 expanded macro variables.
}

Testing Module

Testing.Asymptomatc_identified = (asymptomatic_testing * effectiveness_of_identification)
UNITS: person/day
DOCUMENT: The actual value of Asymptomatic that are identified through contact tracing is given as the product of those tested and the assumed effectiveness of identification via contact tracing
Testing.asymptomatic_testing = MIN(max_asymptomatic_testing_capacity; MIN(SUM_AI_per_day/minimum_time_to_test_a_case; asymptomatic_testing_based_on_contact_tracing))
UNITS: person/day

DOCUMENT: The actual testing of Asymptomatic Infected is equal to whatever is the lowest, either the maximum testing capacity for Asymptomatic, the total number of Asymptomatic that have been traced through contact tracing, or the total number of people that are Asymptomatic Infected (structure by ISEE systems, 2020)
Testing.asymptomatic_testing_based_on_contact_tracing = SWITCH_Contact_Tracing_Activated*(IF TIME < Contact_Tracing_Starttime THEN 0 ELSE recent_testing_positive * over_time_contacts_tested_per_tested_positive_baseline)
UNITS: person/day
DOCUMENT:
structure by ISEE systems, 2020)
Testing.Contact_Tracing_Starttime = 93
UNITS: days
DOCUMENT: Contact tracing is hypothesised to have begun at the beginning of April
Testing.Cumulative_Positive_Tests(t) = Cumulative_Positive_Tests(t - dt) + (testing_positives) * dt
INIT Testing.Cumulative_Positive_Tests = 0
UNITS: People
DOCUMENT: The total number of all confirmed via testing positive cases of COVID-19 in Norway. Increases through the testing positives rate
INFLOWS:
Testing.testing_positives = Main_Infection_Model.Testing_rates_SUM
UNITS: Person/Day
DOCUMENT: The rate of increase in cumulative positive tests. Is equal to the sum of the testing rates for all severity categories.
Testing.effect_of_Testing_Capacity_on_Target_Test_Rate_CCI = GRAPH(Testing_Capacity)
Points(11): (0, 0,000), (1000, 0,33583091167), (2000, 0,560945103841), (3000, 0,7118436595), (4000, 0,812993986277), (5000, 0,880797077978), ...
UNITS: dmnl
DOCUMENT: The hypothesized effect of testing capacity on the target test rate of Critical Care Infected. Infected in this severity category were the most prioritised and, therefore, it is expected to increase steeply
Testing.effect_of_Testing_Capacity_on_Target_Test_Rate_HI = GRAPH(Testing_Capacity)
Points(12): (0, 0,000), (1590,90909091, 0,310543881188), (3181,81818182, 0,526416574697), (4772,72727273, 0,676479166897), (6363,63636364, 0,780794266745), (7954,54545455, 0,853308275045), ...
UNITS: dmnl
DOCUMENT: The hypothesized effect of testing capacity on the target test rate of Hospitalied Infected. It is expected to increase steeply as Testing Capacity increases and to saturate at high levels of capacity.
Testing.effect_of_Testing_Capacity_on_Target_Test_Rate_SI = GRAPH(Testing_Capacity)
Points(11): (0, 0,00669285092428), (1750, 0,0179862099621), (3500, 0,0474258731776), (5250, 0,119202922022), (7000, 0,26894142137), (8750, 0,500), ...

UNITS: dmnl
DOCUMENT: The hypothesized effect of testing capacity on the target test rate of Symptomatic Infected. It is expected to increase slowly at low levels of Testing Capacity and reach it maximum at rather high levels of such capacity.
Testing.effectiveness_of_identification = ,1
UNITS: dmnl
DOCUMENT: Represents the maximum fraction of those tested through contact tracing that might be actually infected. It is assumed here to be constant and equal to 10% of all tested.
Testing.max_asymptomatic_testing_capacity = Testing_Capacity-(symptomatic_HI_testing+symptomatic_CCI_testing+ symptomatic_testing)
UNITS: person/day
DOCUMENT: The maximum testing capacity that remains available for the testing of Asymptomatic Infected is given as the total available capacity minus that which is used for testing of all the more severe categories (structure by ISEE systems, 2020)
Testing.maximum_Target_Test_Rate_CCI = ,85
UNITS: dmnl
DOCUMENT: the maximum fraction of Critical Care infected individuals that can be identified through testing
Testing.maximum_Target_Test_Rate_HI = ,65
UNITS: dmnl
DOCUMENT: the maximum fraction of Hospitalised infected individuals that can be identified through testing
Testing.maximum_Target_Test_Rate_SI = ,45
UNITS: dmnl
DOCUMENT: the maximum fraction of Symptomatic infected individuals that can be identified through testing
Testing.minimum_time_to_test_a_case = 1
UNITS: day
DOCUMENT: The minimum time to test a case is assumed to be 1 day given appropriate capacity in place
Testing.over_time_contacts_tested_per_tested_positive_baseline = GRAPH(TIME)
Points(11): (90,0, 0,00), (117,5, 3,4065749153), (145,0, 6,11863184831), (172,5, 8,27776616674), (200,0, 9,99670537788), (227,5, 11,3651945851), ...
UNITS: dmnl
DOCUMENT: The contacts traced per positive test over time. Contact tracing is assumed to have begun at the beginning of April. We do not have adequate information of how many contacts per positive test are traced in reality and even more so, at different points in time but the baseline assumption assumes a faster rate of increase earlier on that saturates at a maximum of 15 contacts per person
Testing.over_time_contacts_tested_per_tested_positive_test_down = GRAPH(TIME)
Points(11): (90,0, 0,00), (117,5, 0,37), (145,0, 1,21), (172,5, 2,46), (200,0, 3,85), (227,5, 5,35), ...

UNITS: dmnl
DOCUMENT: An alternative assumption of contacts traced per confirmed COVID-19 test. Assumes a slower increase and lower saturation point. Used here for testing purposes
Testing.over_time_contacts_tested_per_tested_positive_test_slower = GRAPH(TIME)
Points(256): (90,0, 0,00), (91,0784313725, 0,00), (92,1568627451, 0,00), (93,2352941176, 0,00), (94,3137254902, 0,08), (95,3921568627, 0,08), ...
UNITS: dmnl
DOCUMENT: An alternative assumption of contacts traced per confirmed COVID-19 test. Assumes a slower increase and the same saturation point as the baseline assumption. Used here for testing purposes
Testing.over_time_contacts_tested_per_tested_positive_test_up = GRAPH(TIME)
Points(11): (90,0, 0,00), (117,5, 11,7540819085), (145,0, 19,6330786344), (172,5, 24,9145280825), (200,0, 28,4547895197), (227,5, 30,8278977292), ...
UNITS: dmnl
DOCUMENT: An alternative assumption of contacts traced per confirmed COVID-19 test. Assumes a similarly steep increase as the baseline assumption but with much higher upper bounds for traced contacts. Used here for testing purposes
Testing.recent_testing_positive = SMTH1(Main_Infection_Model.Testing_rates_SUM; testing_smooth_time; 0) {DELAY CONVERTER}
UNITS: Person/Day
DOCUMENT: For a positive test to lead to traced contacts, it needs to be processed and contacts should be documented. The process represented as a first order smoothing (structure by ISEE systems, 2020)
Testing.SUM_AI_per_day = SUM(Main_Infection_Model.AI_per_day_of_infection)
UNITS: persons
DOCUMENT: The total number of Asymptomatic, non tested, Infected at all days of infection
Testing.SUM_CCI_per_day = SUM(Main_Infection_Model.CCI_per_day_of_infection)
UNITS: persons
DOCUMENT: The total number of Critical Care, non tested, Infected at all days of infection
Testing.SUM_HI_per_day = SUM(Main_Infection_Model.HI_per_day_of_infection)
UNITS: persons
DOCUMENT: The total number of Hospitalised, non tested, Infected at all days of infection
Testing.SUM_SI_per_day = SUM(Main_Infection_Model.SI_per_day_of_infection)
UNITS: people
DOCUMENT: The total number of Symptomatic, non tested, Infected at all days of infection
Testing.SWITCH_Contact_Tracing_Activated = 1
UNITS: dmnl
Testing.symptomatic_CCI_testing = MIN(Testing_Capacity; (SUM_CCI_per_day/minimum_time_to_test_a_case) * Target_Test_Rate_CCI)
UNITS: PErson/Day

DOCUMENT: The actual testing of Critical Care Infected is equal to whatever is the lowest, either the testing capacity, or the total number of people at this category multiplied by the target test rate (structure by ISEE systems, 2020)
Testing.symptomatic_HI_testing = MIN(Testing_Capacity-symptomatic_CCI_testing; (SUM_HI_per_day/minimum_time_to_test_a_case) * Target_Test_Rate_HI)
UNITS: PErson/Day
DOCUMENT: The actual testing of Hospitalised Infected is equal to whatever is the lowest, either the testing capacity (minus that which is used for the more severely infected), or the total number of people at this category multiplied by the target test rate (structure by ISEE systems, 2020)
Testing.symptomatic_testing = MIN(Testing_Capacity-symptomatic_HI_testing-symptomatic_CCI_testing; (SUM_SI_per_day/minimum_time_to_test_a_case) * Target_Test_Rate_SI)
UNITS: person/day
DOCUMENT: The actual testing of Symptomatic Infected is equal to whatever is the lowest, either the testing capacity (minus that which is used for the more severely infected), or the total number of people at this category multiplied by the target test rate (structure by ISEE systems, 2020)
Testing.Target_Test_Rate_CCI = effect_of_Testing_Capacity_on_Target_Test_Rate_CCI*maximum_Target_Test_Rate_CCI
UNITS: dmnl
DOCUMENT: The total Target Test Rate CCI represents the maximum fraction of Critical Care infected that can be identified through testing. It is the product of the effect of testing capacity on target test rate for this category (given on a scale from 0 to 1) and the actual maximum fraction that can be reached through testing
Testing.Target_Test_Rate_HI = effect_of_Testing_Capacity_on_Target_Test_Rate_HI*maximum_Target_Test_Rate_HI
UNITS: dmnl
DOCUMENT: The total Target Test Rate HI represents the maximum fraction of Hospitalised infected that can be identified through testing. It is the product of the effect of testing capacity on target test rate for this category (given on a scale from 0 to 1) and the actual maximum fraction that can be reached through testing
Testing.Target_Test_Rate_SI = effect_of_Testing_Capacity_on_Target_Test_Rate_SI*maximum_Target_Test_Rate_SI
UNITS: dmnl
DOCUMENT: The total Target Test Rate SI represents the maximum fraction of Symptomatic infected that can be identified through testing. It is the product of the effect of testing capacity on target test rate for this category (given on a scale from 0 to 1) and the actual maximum fraction that can be reached through testing
Testing.test_rate_A! = Asymptomatc_identified//SUM_AI_per_day
INIT Testing.test_rate_A! = 0
UNITS: dmnl/day
DOCUMENT: The test rate, in fractional terms, is given as the ratio of the infected that we can test over the all non-tested, infected individuals at this severity category
Testing.test_rate_CCI = symptomatic_CCI_testing // SUM_CCI_per_day

INIT Testing.test_rate_CCI = 0
UNITS: 1/Days
DOCUMENT: The test rate, in fractional terms, is given as the ratio of the infected that we can test over the all non-tested, infected individuals at this severity category
Testing.test_rate_HI = symptomatic_HI_testing // SUM_HI_per_day
INIT Testing.test_rate_HI = 0
UNITS: 1/Days
DOCUMENT: The test rate, in fractional terms, is given as the ratio of the infected that we can test over the all non-tested, infected individuals at this severity category
Testing.test_rate_SI = symptomatic_testing // SUM_SI_per_day
INIT Testing.test_rate_SI = 0
UNITS: 1/Days
DOCUMENT: The test rate, in fractional terms, is given as the ratio of the infected that we can test over the all non-tested, infected individuals at this severity category
Testing.Testing_Capacity(t) = Testing_Capacity(t - dt) + (change_in_Testing_Capacity) * dt
INIT Testing.Testing_Capacity = 0
UNITS: People/Day
DOCUMENT: The capacity for COVID-19 testing (how many people per day can Norway test). It is a stock increasing through the change in testing capacity
INFLOWS:
Testing.change_in_Testing_Capacity = (IF TIME > 50 AND TIME < 100 THEN (Testing_Capacity_daily_addition) ELSE 0)
UNITS: (People/Day)/Day
DOCUMENT: The daily increase in testing capacity is equal to the daily addition of tests
Testing.Testing_Capacity_daily_addition = 200
UNITS: (People/Day)/Day
DOCUMENT: The daily addition of test is assumed to be 200.
Testing.testing_smooth_time = 7
UNITS: Days
DOCUMENT: The average time for a testing result to be processed, perceived, and lead to the tracing of contacts.
********** Testing.DATA_NORWAY: **********
Testing."Positive_tests_by_sp._coll_day_DATA_june" = GRAPH(TIME)
Points(116): (53,0, 0,0), (54,0, 0,0), (55,0, 0,0), (56,0, 2,0), (57,0, 2,0), (58,0, 3,0), ...
UNITS: person/day

DOCUMENT: "Number of tested persons per specimen collection date and number of positive results" (FHI, 2020). Accessed 02.05.2020
Testing."TOTAL_tests_by_sp._coll_day_DATA_june_2" = GRAPH(TIME)
Points(116): (53,0, 0,0), (54,0, 12,0), (55,0, 62,0), (56,0, 148,0), (57,0, 249,0), (58,0, 290,0), ...
UNITS: person/day
DOCUMENT: "Number of tested persons per specimen collection date and number of positive results" (FHI, 2020). Accessed 02.05.2020
Testing.Cumulative_Positive_Tests_DATA(t) = Cumulative_Positive_Tests_DATA(t - dt) + (testing_positives_DATA) * dt
INIT Testing.Cumulative_Positive_Tests_DATA = 0
UNITS: People
DOCUMENT: The, according to data, total number of all confirmed via testing positive cases of COVID-19 in Norway. Increases through the testing positives rate
INFLOWS:
Testing.testing_positives_DATA = "Positive_tests_by_sp._coll_day_DATA_june"
UNITS: Person/Day
{ The model has 48 (224) variables (array expansion in parens).
In this module and 0 additional modules with 1 sectors.
Stocks: 3 (3) Flows: 3 (3) Converters: 42 (218)
Constants: 9 (9) Equations: 36 (212) Graphicals: 9 (9)
There are also 141 expanded macro variables.
}

Main Infection Model

Main_Infection_Model.AI_avg_duration_of_infection_2 = 20
UNITS: days
DOCUMENT: The average duration of infection for an Asymptomatic individual is assumed to be 20 days. Estimates by Bi et al., 2020
Main_Infection_Model.AI_Recent_Recovered(t) = AI_Recent_Recovered(t - dt) + (Recovery_AI_s3 + Recovery_AI_s2 + Recovery_AI_s1 - Flow_143) * dt {CONVEYOR}
INIT Main_Infection_Model.AI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People

DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Recovery_AI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_AI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_AI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_143 = CONVEYOR OUTFLOW

UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.AI_Recovered(t) = AI_Recovered(t - dt) + (Flow_143 + inf_end_AI_s2 + inf_end_AI_s3 + inf_end_AI_s1) * dt
INIT Main_Infection_Model.AI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_143 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.inf_end_AI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_AI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_AI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.AI_recovery_time_distribution_per_flow = AI_avg_duration_of_infection_2/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the recovery time for individuals at each sub-stage.
Main_Infection_Model.AI_s2(t) = AI_s2(t - dt) + (AI_s2_rate - inf_end_AI_s2 - Testing_AI_s2 - AI_s3_rate - Recovery_AI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.AI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.AI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE

LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_AI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Testing_AI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_A!
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.AI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_AI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day

DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.AI_s3(t) = AI_s3(t - dt) + (AI_s3_rate - inf_end_AI_s3 - Testing_AI_s3 - becoming_Symptomatic_Infected - Recovery_AI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.AI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.AI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_AI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Testing_AI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_A!
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.becoming_Symptomatic_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE

OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_AI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.AI_time_to_become_SI_distribution_per_flow = avg_incubation_period/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the time to progress to a more severe stage for an average individual at each sub-stage.
Main_Infection_Model.Asymptomatic_Infected(t) = Asymptomatic_Infected(t - dt) + (becoming_infectious + Imported_Cases - inf_end_AI_s1 - Testing_AI_s1 - AI_s2_rate - Recovery_AI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Asymptomatic_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Infected persons who do not show any symptoms associated with COVID-19. The stock of Asymptomatic Infected increases through the Infection Rate and decreases through Recovery, Testing, or progression to the next stage of the disease (AI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_infectious = CONVEYOR OUTFLOW
INFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Imported_Cases = (Daily_Recorded_Imported_Cases_UTLAND+ (,4*Daily_Recorded_Imported_Cases_UTLAND)) {UNIFLOW}
INFLOW PRIORITY: 2
UNITS: person/day

DOCUMENT: The rate of imported cases introduced to Norway per day. The imported cases are assumed to directly enter the Infected (and infectious) Population from the first stage of infection, that is, the distribution of imported cases at different stages and days of infection is not considered. We also assume a (perhaps very moderate) additional 40% of confirmed cases as never tested.
NOT SURE CLEAR
OUTFLOWS:
Main_Infection_Model.inf_end_AI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Testing_AI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_A!
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.AI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_AI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.avg_incubation_period = 4

UNITS: days
DOCUMENT: The average incubation period (time from infection to development of symptoms) ranges from around 4 to 6 days (M. Park, Cook, Lim, Sun, & Dickens, 2020). Due to a 2-days discrete latency period, we use lower bound of 4 days.
Main_Infection_Model.AVG_STAY_IN_CRITICAL_CARE_BEFORE_DEATH = 12
UNITS: days
DOCUMENT: For the average duration of a Critical Care admission, we used the 12-day estimate from the two developed Norwegian models (Norwegian Institute of Public Health - FHI, 2020a; NTNU COVID-19 Taskforce, 2020).
Main_Infection_Model.AVG_STAY_IN_CRITICAL_CARE_BEFORE_RECOVERY = 10*0 +12*1
UNITS: days
DOCUMENT: For the average duration of a Critical Care admission, we used the 12-day estimate from the two developed Norwegian models (Norwegian Institute of Public Health - FHI, 2020a; NTNU COVID-19 Taskforce, 2020).
Main_Infection_Model.avg_stay_in_hospital_before_CC_admission = 3
UNITS: days
DOCUMENT: The average duration of hospitalisation for patients who eventually get admitted to Critical Care units is 3 days. This time period was used by Tuite et al., (2020 based on estimates by Wang et al., 2020). Models in the Norwegian population optimise for a 4-day period (NTNU COVID-19 Taskforce, 2020); (Norwegian Institute of Public Health - FHI, 2020a).
Main_Infection_Model.AVG_STAY_IN_HOSPITAL_BEFORE_DEATH = 8
UNITS: days
DOCUMENT: The average stay in hospital for patients dying without a Critical Care admission is equal to the time the same patients would recover. The 8-day period is in accordance with values used by the Norwegian Institute of Public Health - FHI, (2020a) and by Ferguson et al., (2020)
Main_Infection_Model.avg_stay_in_hospital_no_CC_admission = 8
UNITS: days
DOCUMENT: The average stay in hospital for patients recovering without the need for Critical Care Admission. An 8-day period was chosen in accordance with models applied to the norwegian population (Norwegian Institute of Public Health - FHI, 2020a; NTNU COVID-19 Taskforce, 2020)
Main_Infection_Model.AVG_time_to_become_more_severely_ill = 5*1+ (5/2)*0
UNITS: days
Main_Infection_Model.avg_time_to_hospitalisation_after_symptom_onset = 5
UNITS: days
DOCUMENT: The average time from symptom onset to hospitalisation varies in different countries and even different time period of the COVID-19 spread in the same country. We use the 5 days assumption used by Ferguson et al. (2020) and Struben (2020).
Main_Infection_Model.CCI_Dead(t) = CCI_Dead(t - dt) + (Flow_140) * dt

INIT Main_Infection_Model.CCI_Dead = 0
UNITS: People
DOCUMENT: The total number of people who have died from this severity category in the "long-term" (after the end of their stay in the "recent dead" stock)
INFLOWS:
Main_Infection_Model.Flow_140 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.CCI_Recent_Dead(t) = CCI_Recent_Dead(t - dt) + (Dying_CCI_s3 + Dying_CCI_s2 + Dying_CCI_s1 - Flow_140) * dt {CONVEYOR}
INIT Main_Infection_Model.CCI_Recent_Dead = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently died from this severity category. Dead individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Dying_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.

Main_Infection_Model.Dying_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_140 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.CCI_Recent_Recovered(t) = CCI_Recent_Recovered(t - dt) + (Recovery_CCI_s3 + Recovery_CCI_s2 + Recovery_CCI_s1 - Flow_135) * dt {CONVEYOR}
INIT Main_Infection_Model.CCI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Recovery_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow

EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_135 = CONVEYOR OUTFLOW
UNITS: person/day
Main_Infection_Model.CCI_Recovered(t) = CCI_Recovered(t - dt) + (Flow_135 + inf_end_CCI_s2 + inf_end_CCI_s3 + inf_end_CCI_s1) * dt
INIT Main_Infection_Model.CCI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_135 = CONVEYOR OUTFLOW
UNITS: person/day
Main_Infection_Model.inf_end_CCI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_CCI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_CCI_s1 = CONVEYOR OUTFLOW

OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.CCI_recovery_time_distribution_per_flow = AVG_STAY_IN_CRITICAL_CARE_BEFORE_RECOVERY/number_of_stages
UNITS: days
Main_Infection_Model.CCI_s2(t) = CCI_s2(t - dt) + (CCI_s2_rate - inf_end_CCI_s2 - Dying_CCI_s2 - Testing_CCI_s2 - CCI_s3_rate - Recovery_CCI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.CCI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.CCI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_CCI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Testing_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_CCI

EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
Main_Infection_Model.CCI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.CCI_s3(t) = CCI_s3(t - dt) + (CCI_s3_rate - inf_end_CCI_s3 - Dying_CCI_s3 - Testing_CCI_s3 - Recovery_CCI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.CCI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.CCI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE

LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_CCI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Testing_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_CCI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
Main_Infection_Model.Recovery_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.

Main_Infection_Model.CCI_time_spent_before_death_distribution_per_flow = AVG_STAY_IN_CRITICAL_CARE_BEFORE_DEATH/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category before death is divided by the number of sub-stages of the category to give the value of the time spent before death for each of the sub-stages
Main_Infection_Model.Critical_Care_Infected(t) = Critical_Care_Infected(t - dt) + (becoming_Critical_Care_Infected - inf_end_CCI_s1 - Dying_CCI_s1 - Testing_CCI_s1 - CCI_s2_rate - Recovery_CCI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Critical_Care_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Infected persons who are in critical care due to a COVID-19 infection. The stock of Critical Care Infected increases through the becoming Critical Care Infected rate and decreases through Recovery, Testing, or progression to the next stage of the disease (CCI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_Critical_Care_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_CCI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 2
UNITS: person/day

DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Testing_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_CCI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
Main_Infection_Model.CCI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Daily_Recorded_Imported_Cases_UTLAND = GRAPH(TIME+2)
Points(151): (0,0, 0,0), (1,0, 0,0), (2,0, 0,0), (3,0, 0,0), (4,0, 0,0), (5,0, 0,0), ...
UNITS: People/Day
DOCUMENT: Developed based on data from FHIs daily reports. The 1st reported infection (by testing day) was the 21st of February (model time 51). We assume a 4-day delay in this identification and introduce the first case on the 17th of February (model time 47). Due to the lack of reporting between the first case (21.02) and the initiation of the Daily Reports (08.03), we extrapolated those points using a power trendline (R^2 = 0,8721). To improve fit, we only used the first 22 data-points for the extrapolation (missing datapoints 5 to 16).

An exponential trendline, while giving higher R^2 seems unlikely as it might underrepresent the initial imported case. Due to an overestimation at the first extrapolated data points, the value of the actual confirmed cases data were used instead of the extrapolated ones.
Main_Infection_Model.Exposed_Non_Contagious(t) = Exposed_Non_Contagious(t - dt) + (Infection_Rate - becoming_infectious) * dt {CONVEYOR}
INIT Main_Infection_Model.Exposed_Non_Contagious = 0
TRANSIT TIME = 2
INFLOW LIMIT = INF
CAPACITY = INF
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of people who are infected with the disease but are not yet contagious. It increases as people get infected and decreases as people become infectious. The total transit time, the time each individual spends in the non-contagious stage, is assumed to be 2 days
INFLOWS:
Main_Infection_Model.Infection_Rate = Infectivity_Calc.Infection_Rate_SUM {UNIFLOW}
UNITS: person/day
DOCUMENT: The rate of infections per day. The Infection rate is the sum of all possible infections for infected according to their infectivity profile (see Infectivity Module variables for more details).
OUTFLOWS:
Main_Infection_Model.becoming_infectious = CONVEYOR OUTFLOW
INFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.fraction_AI_becoming_SI = ,6*0 +,55*1
UNITS: dmnl
DOCUMENT: The fraction of the Asymptomatic Infected that will eventually develop symptoms. Estimates of the proportion of infections that remain asymptomatic range from 5% to 80% (for a quick review, see Heneghan, Brassey, & Jefferson, 2020) but commonly used values are closer to 35-50% (Ferguson et al., 2020; Ferretti et al., 2020; Norwegian Institute of Public Health - FHI, 2020; NTNU COVID-19 Taskforce, 2020). Here, we assume that 45% of infections will remain asymptomatic, hence the fraction of Asymptomatic Infected that will become Symptomatic is assumed to be 55%.
Main_Infection_Model.fraction_AI_recovering = (1-fraction_AI_becoming_SI)
UNITS: dmnl
Main_Infection_Model.fraction_becoming_more_severy = 2/5
UNITS: dmnl
Main_Infection_Model.fraction_CCI_dying = ,5*0 + 1/5
UNITS: dmnl

Main_Infection_Model.fraction_CCI_recovering = (1-fraction_CCI_dying)
UNITS: dmnl
DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the recovery time for individuals at each sub-stage.
Main_Infection_Model.fraction_HI_becoming_CCI = ,45
UNITS: dmnl
DOCUMENT: The fraction of the Hospitalised Infected that are assumed to enter Critical Care. The value of 40% accounts for 11% of all infected. Values used in epidemiological models are relatively lower (e.g. 30% in Ferguson et al., 2020; NTNU COVID-19 Taskforce, 2020), however, those parameters are dependent to some extent to the structure used in these models.
Main_Infection_Model.fraction_HI_dying = ,01*0 + 0,01
UNITS: dmnl
Main_Infection_Model.fraction_HI_recovering = (1-fraction_HI_dying)
UNITS: dmnl
Main_Infection_Model.fraction_SI_becoming_HI = ,4
UNITS: dmnl
DOCUMENT: The fraction of the Symptomatic Infected that are assumed to become hospitalised. The value of 40% accounts for 22% of all infected. Estimates are closer to 16-17% (e.g. Gaythorpe et al., 2020; Homer, 2020), however there are expected to be some discrepancies due to the structural components of our model
Main_Infection_Model.fraction_SI_recovering = 1-fraction_SI_becoming_HI
UNITS: dmnl
Main_Infection_Model.HI_Dead(t) = HI_Dead(t - dt) + (Flow_158) * dt
INIT Main_Infection_Model.HI_Dead = 0
UNITS: People
DOCUMENT: The total number of people who have died from this severity category in the "long-term" (after the end of their stay in the "recent dead" stock)
INFLOWS:
Main_Infection_Model.Flow_158 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.HI_Recent_Dead(t) = HI_Recent_Dead(t - dt) + (Dying_HI_s3 + Dying_HI_s2 + Dying_HI_s1 - Flow_158) * dt {CONVEYOR}
INIT Main_Infection_Model.HI_Recent_Dead = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People

DOCUMENT: The total number of people who have recently died from this severity category. Dead individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Dying_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_158 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)

Main_Infection_Model.HI_Recent_Recovered(t) = HI_Recent_Recovered(t - dt) + (Recovery_HI_s3 + Recovery_HI_s2 + Recovery_HI_s1 - Flow_157) * dt {CONVEYOR}
INIT Main_Infection_Model.HI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Recovery_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3

OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_157 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.HI_Recovered(t) = HI_Recovered(t - dt) + (Flow_157 + inf_end_HI_s2 + inf_end_HI_s3 + inf_end_HI_s1) * dt
INIT Main_Infection_Model.HI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_157 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.inf_end_HI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_HI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_HI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.HI_recovery_time_distribution_per_flow = avg_stay_in_hospital_no_CC_admission/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the recovery time for individuals at each sub-stage.
Main_Infection_Model.HI_s2(t) = HI_s2(t - dt) + (HI_s2_rate - inf_end_HI_s2 - Dying_HI_s2 - Testing_HI_s2 - HI_s3_rate - Recovery_HI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.HI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"

CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.HI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_HI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Testing_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_HI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.HI_s3_rate = LEAKAGE OUTFLOW

LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.HI_s3(t) = HI_s3(t - dt) + (HI_s3_rate - inf_end_HI_s3 - Dying_HI_s3 - Testing_HI_s3 - becoming_Critical_Care_Infected - Recovery_HI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.HI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.HI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:

Main_Infection_Model.inf_end_HI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Testing_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_HI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.becoming_Critical_Care_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1

OUTFLOW PRIORITY: 5
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.HI_time_spent_before_death_distribution_per_flow = AVG_STAY_IN_HOSPITAL_BEFORE_DEATH/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category before death is divided by the number of sub-stages of the category to give the value of the time spent before death for each of the sub-stages
Main_Infection_Model.HI_time_to_become_CCI_distribution_per_flow = avg_stay_in_hospital_before_CC_admission/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the time to progress to a more severe stage for an average individual at each sub-stage.
Main_Infection_Model.Hospitalised_Infected(t) = Hospitalised_Infected(t - dt) + (becoming_Hospitalised_Infected - inf_end_HI_s1 - Dying_HI_s1 - Testing_HI_s1 - HI_s2_rate - Recovery_HI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Hospitalised_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Infected persons who are hospitalised due to a COVID-19 infection. The stock of Hospitalsied Infected increases through the becoming Hospitalised Infected rate and decreases through Recovery, Testing, or progression to the next stage of the disease (HI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_Hospitalised_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_HI_s1 = CONVEYOR OUTFLOW

OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Testing_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_HI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.HI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 5

UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.number_of_stages = 3
UNITS: dmnl
DOCUMENT: The number of stages at each severity category
Main_Infection_Model.SI_avg_duration_of_infection_3 = 16
UNITS: days
DOCUMENT: We assume due to lack of evidence to the contrary that Asymptomatic and Symptomatic will have the same duration of infection of total 20 days. With an estimated average duration of infection for Asymptomatic Infected of 20 days and an average incubation period of 4 days, the average duration of infection for a Symptomatic Infected person is 16 days.
Main_Infection_Model.SI_Recent_Recovered(t) = SI_Recent_Recovered(t - dt) + (Recovery_SI_s3 + Recovery_SI_s2 + Recovery_SI_s1 - Flow_150) * dt {CONVEYOR}
INIT Main_Infection_Model.SI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Recovery_SI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_SI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%

CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_SI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_150 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.SI_Recovered(t) = SI_Recovered(t - dt) + (Flow_150 + inf_end_SI_s2 + inf_end_SI_s3 + inf_end_SI_s1) * dt
INIT Main_Infection_Model.SI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_150 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.inf_end_SI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_SI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1

UNITS: person/day
Main_Infection_Model.inf_end_SI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.SI_recovery_time_distribution_per_flow = SI_avg_duration_of_infection_3/number_of_stages
UNITS: days
DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the recovery time for individuals at each sub-stage.
Main_Infection_Model.SI_s2(t) = SI_s2(t - dt) + (SI_s2_rate - inf_end_SI_s2 - Testing_SI_s2 - SI_s3_rate - Recovery_SI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.SI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.SI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_SI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Testing_SI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_SI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day

DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.SI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_SI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.SI_s3(t) = SI_s3(t - dt) + (SI_s3_rate - inf_end_SI_s3 - Testing_SI_s3 - becoming_Hospitalised_Infected - Recovery_SI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.SI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.SI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage

OUTFLOWS:
Main_Infection_Model.inf_end_SI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Testing_SI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_SI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.becoming_Hospitalised_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_SI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.SI_time_to_become_HI_distribution_per_flow = avg_time_to_hospitalisation_after_symptom_onset/number_of_stages
UNITS: days

DOCUMENT: The total duration individuals spend at this severity category is divided by the number of sub-stages of the category to give the value of the time to progress to a more severe stage for an average individual at each sub-stage.
Main_Infection_Model.Susceptible(t) = Susceptible(t - dt) + (- Infection_Rate) * dt
INIT Main_Infection_Model.Susceptible = NORWAY_INIT_POP
UNITS: People
DOCUMENT: The Population that is Susceptible to an infection by COVID-19. The Susceptible Population decreases through the infection rate as people get infected with the virus. The initial Susceptible Population is the entire population of Norway, and births or deaths with cause other than COVID are not considered here.
OUTFLOWS:
Main_Infection_Model.Infection_Rate = Infectivity_Calc.Infection_Rate_SUM {UNIFLOW}
UNITS: person/day
DOCUMENT: The rate of infections per day. The Infection rate is the sum of all possible infections for infected according to their infectivity profile (see Infectivity Module variables for more details).
Main_Infection_Model.Symptomatic_Infected(t) = Symptomatic_Infected(t - dt) + (becoming_Symptomatic_Infected - inf_end_SI_s1 - Testing_SI_s1 - SI_s2_rate - Recovery_SI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Symptomatic_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Infected persons who show symptoms associated with COVID-19. The stock of Symptomatic Infected increases through the becoming Symptomatic Infected rate and decreases through Recovery, Testing, or progression to the next stage of the disease (SI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_Symptomatic_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
OUTFLOWS:
Main_Infection_Model.inf_end_SI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day

Main_Infection_Model.Testing_SI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_SI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
Main_Infection_Model.SI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_SI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.T_AI_Recent_Recovered(t) = T_AI_Recent_Recovered(t - dt) + (Recovery_T_AI_s3 + Recovery_T_AI_s2 + Recovery_T_AI_s1 - Flow_161) * dt {CONVEYOR}
INIT Main_Infection_Model.T_AI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People

DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Recovery_T_AI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_AI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_AI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_161 = CONVEYOR OUTFLOW

UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.T_AI_Recovered(t) = T_AI_Recovered(t - dt) + (Flow_161 + inf_end_T_AI_s2 + inf_end_T_AI_s3 + inf_end_T_AI_s1) * dt
INIT Main_Infection_Model.T_AI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_161 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.inf_end_T_AI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_AI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_AI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_AI_s2(t) = T_AI_s2(t - dt) + (T_AI_s2_rate + Testing_AI_s2 - inf_end_T_AI_s2 - T_AI_s3_rate - Recovery_T_AI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.T_AI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_AI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day

DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_AI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_A!
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_AI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_AI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_AI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.T_AI_s3(t) = T_AI_s3(t - dt) + (T_AI_s3_rate + Testing_AI_s3 - inf_end_T_AI_s3 - becoming_Tested_Symptomatic_Infected - Recovery_T_AI_s3) * dt {CONVEYOR}

INIT Main_Infection_Model.T_AI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_AI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_AI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_A!
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_AI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.becoming_Tested_Symptomatic_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day

DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_AI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.T_CCI_Dead(t) = T_CCI_Dead(t - dt) + (Flow_160) * dt
INIT Main_Infection_Model.T_CCI_Dead = 0
UNITS: People
DOCUMENT: The total number of people who have died from this severity category in the "long-term" (after the end of their stay in the "recent dead" stock)
INFLOWS:
Main_Infection_Model.Flow_160 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.T_CCI_Recent_Dead(t) = T_CCI_Recent_Dead(t - dt) + (Dying_T_CCI_s3 + Dying_T_CCI_s1 + Dying_T_CCI_s2 - Flow_160) * dt {CONVEYOR}
INIT Main_Infection_Model.T_CCI_Recent_Dead = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently died from this severity category. Dead individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Dying_T_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1

OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_T_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_T_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_160 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.T_CCI_Recent_Recovered(t) = T_CCI_Recent_Recovered(t - dt) + (Recovery_T_CCI_s3 + Recovery_T_CCI_s2 + Recovery_T_CCI_s1 - Flow_159) * dt {CONVEYOR}
INIT Main_Infection_Model.T_CCI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious

INFLOWS:
Main_Infection_Model.Recovery_T_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_159 = CONVEYOR OUTFLOW
UNITS: person/day
Main_Infection_Model.T_CCI_Recovered(t) = T_CCI_Recovered(t - dt) + (Flow_159 + inf_end_T_CCI_s2 + inf_end_T_CCI_s3 + inf_end_T_CCI_s1) * dt

INIT Main_Infection_Model.T_CCI_Recovered = 0
UNITS: People
INFLOWS:
Main_Infection_Model.Flow_159 = CONVEYOR OUTFLOW
UNITS: person/day
Main_Infection_Model.inf_end_T_CCI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_CCI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_CCI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_CCI_s2(t) = T_CCI_s2(t - dt) + (T_CCI_s2_rate + Testing_CCI_s2 - inf_end_T_CCI_s2 - T_CCI_s3_rate - Dying_T_CCI_s2 - Recovery_T_CCI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.T_CCI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_CCI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_CCI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2

OUTFLOW PRIORITY: 3
UNITS: person/day
OUTFLOWS:
Main_Infection_Model.inf_end_T_CCI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_CCI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Dying_T_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Recovery_T_CCI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.

Main_Infection_Model.T_CCI_s3(t) = T_CCI_s3(t - dt) + (T_CCI_s3_rate + Testing_CCI_s3 - inf_end_T_CCI_s3 - Dying_T_CCI_s3 - Recovery_T_CCI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.T_CCI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_CCI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_CCI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
OUTFLOWS:
Main_Infection_Model.inf_end_T_CCI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_T_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day

DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Recovery_T_CCI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.T_HI_Dead(t) = T_HI_Dead(t - dt) + (Flow_164) * dt
INIT Main_Infection_Model.T_HI_Dead = 0
UNITS: People
DOCUMENT: The total number of people who have died from this severity category in the "long-term" (after the end of their stay in the "recent dead" stock)
INFLOWS:
Main_Infection_Model.Flow_164 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.T_HI_Recent_Dead(t) = T_HI_Recent_Dead(t - dt) + (Dying_T_HI_s3 + Dying_T_HI_s1 + Dying_T_HI_s2 - Flow_164) * dt {CONVEYOR}
INIT Main_Infection_Model.T_HI_Recent_Dead = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently died from this severity category. Dead individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Dying_T_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1

OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_T_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Dying_T_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_164 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently dead individuals to the "long-term" dead stock after the end of the transit time (45 days)
Main_Infection_Model.T_HI_Recent_Recovered(t) = T_HI_Recent_Recovered(t - dt) + (Recovery_T_HI_s3 + Recovery_T_HI_s2 + Recovery_T_HI_s1 - Flow_163) * dt {CONVEYOR}
INIT Main_Infection_Model.T_HI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious

INFLOWS:
Main_Infection_Model.Recovery_T_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:
Main_Infection_Model.Flow_163 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)

Main_Infection_Model.T_HI_Recovered(t) = T_HI_Recovered(t - dt) + (Flow_163 + inf_end_T_HI_s2 + inf_end_T_HI_s3 + inf_end_T_HI_s1) * dt
INIT Main_Infection_Model.T_HI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_163 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.inf_end_T_HI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_HI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_HI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_HI_s2(t) = T_HI_s2(t - dt) + (T_HI_s2_rate + Testing_HI_s2 - inf_end_T_HI_s2 - Dying_T_HI_s2 - T_HI_s3_rate - Recovery_T_HI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.T_HI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_HI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage

Main_Infection_Model.Testing_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_HI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_HI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_T_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.T_HI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_HI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%

CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.T_HI_s3(t) = T_HI_s3(t - dt) + (T_HI_s3_rate + Testing_HI_s3 - inf_end_T_HI_s3 - Dying_T_HI_s3 - becoming_Tested_Critical_Care_Infected - Recovery_T_HI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.T_HI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_HI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_HI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_HI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1

UNITS: person/day
Main_Infection_Model.Dying_T_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.becoming_Tested_Critical_Care_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_HI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.T_SI_Recent_Recovered(t) = T_SI_Recent_Recovered(t - dt) + (Recovery_T_SI_s3 + Recovery_T_SI_s2 + Recovery_T_SI_s1 - Flow_162) * dt {CONVEYOR}
INIT Main_Infection_Model.T_SI_Recent_Recovered = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES

UNITS: People
DOCUMENT: The total number of people who have recently recovered from this severity category. Recovered individuals remain in this stock until 45 days (=transit time) have passed since they became infectious
INFLOWS:
Main_Infection_Model.Recovery_T_SI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_SI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Recovery_T_SI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
OUTFLOWS:

Main_Infection_Model.Flow_162 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.T_SI_Recovered(t) = T_SI_Recovered(t - dt) + (Flow_162 + inf_end_T_SI_s2 + inf_end_T_SI_s3 + inf_end_T_SI_s1) * dt
INIT Main_Infection_Model.T_SI_Recovered = 0
UNITS: People
DOCUMENT: The total number of people who have recovered from this severity category in the "long-term" (after the end of their stay in the "recent recovered" stock)
INFLOWS:
Main_Infection_Model.Flow_162 = CONVEYOR OUTFLOW
UNITS: person/day
DOCUMENT: The drop-off flow transports recently recovered individuals to the "long-term" recovered stock after the end of the transit time (45 days)
Main_Infection_Model.inf_end_T_SI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_SI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.inf_end_T_SI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_SI_s2(t) = T_SI_s2(t - dt) + (TSI_s2_rate + Testing_SI_s2 - inf_end_T_SI_s2 - T_SI_s3_rate - Recovery_T_SI_s2) * dt {CONVEYOR}
INIT Main_Infection_Model.T_SI_s2 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.TSI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2

UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_SI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_SI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_SI_s2 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_SI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_SI_s2 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.

Main_Infection_Model.T_SI_s3(t) = T_SI_s3(t - dt) + (T_SI_s3_rate + Testing_SI_s3 - inf_end_T_SI_s3 - becoming_Tested_Hospitalised_Infected - Recovery_T_SI_s3) * dt {CONVEYOR}
INIT Main_Infection_Model.T_SI_s3 = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
INFLOWS:
Main_Infection_Model.T_SI_s3_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_SI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_SI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_SI_s3 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.becoming_Tested_Hospitalised_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2

UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_SI_s3 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Tested_Asymptomatic_Infected(t) = Tested_Asymptomatic_Infected(t - dt) + (Testing_AI_s1 - inf_end_T_AI_s1 - T_AI_s2_rate - Recovery_T_AI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Tested_Asymptomatic_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Infected persons who do not show any symptoms associated with COVID-19. The stock of Tested Asymptomatic Infected increases through the testing rate for Asymptomatic at this stage and decreases through Recovery or progression to the next stage of the disease (T AI s2 rate).
INFLOWS:
Main_Infection_Model.Testing_AI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_A!
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_AI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_AI_s2_rate = LEAKAGE OUTFLOW

LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_AI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_recovering/AI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Tested_Critical_Care_Infected(t) = Tested_Critical_Care_Infected(t - dt) + (becoming_Tested_Critical_Care_Infected + Testing_CCI_s1 - inf_end_T_CCI_s1 - T_CCI_s2_rate - Dying_T_CCI_s1 - Recovery_T_CCI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Tested_Critical_Care_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Tested Infected who are in critical care due to a COVID-19 infection. The stock of Critical Care Infected increases either through the testing rate or through the becoming Hospitalised Infected rate and decreases through Recovery, Dying, or progression to the next stage of the disease (T CCI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_Tested_Critical_Care_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1

OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_CCI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
OUTFLOWS:
Main_Infection_Model.inf_end_T_CCI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.T_CCI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_becoming_more_severy/AVG_time_to_become_more_severely_ill
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Dying_T_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_dying/CCI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.Recovery_T_CCI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_CCI_recovering/CCI_recovery_time_distribution_per_flow

EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Tested_Hospitalised_Infected(t) = Tested_Hospitalised_Infected(t - dt) + (becoming_Tested_Hospitalised_Infected + Testing_HI_s1 - inf_end_T_HI_s1 - Dying_T_HI_s1 - T_HI_s2_rate - Recovery_T_HI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Tested_Hospitalised_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Tested Infected persons who are hospitalised due to a COVID-19 infection. The stock of Tested Hospitalsied Infected increases either through the testing rate or through the becoming Hospitalised Infected rate and decreases through Recovery, Dying, or progression to the next stage of the disease (T HI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_Tested_Hospitalised_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_HI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 3

UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_HI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.Dying_T_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_dying/HI_time_spent_before_death_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage die. It is represented as a material delay given by the fraction of infected dying over the avg time before death for this particular outflow.
Main_Infection_Model.T_HI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_becoming_CCI/HI_time_to_become_CCI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_HI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_HI_recovering/HI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 4
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.

Main_Infection_Model.Tested_Symptomatic_Infected(t) = Tested_Symptomatic_Infected(t - dt) + (becoming_Tested_Symptomatic_Infected + Testing_SI_s1 - inf_end_T_SI_s1 - TSI_s2_rate - Recovery_T_SI_s1) * dt {CONVEYOR}
INIT Main_Infection_Model.Tested_Symptomatic_Infected = 0
TRANSIT TIME = "transit_time_-_max_duration_of_infection"
CONTINUOUS
ACCEPT MULTIPLE BATCHES
UNITS: People
DOCUMENT: The stock of Tested Symptomatic Infected persons who show symptoms associated with COVID-19. The stock of Tested Symptomatic Infected increases either through the testing rate or through the becoming Symptomatic Infected rate and decreases through Recovery or progression to the next stage of the disease (T SI s2 rate).
INFLOWS:
Main_Infection_Model.becoming_Tested_Symptomatic_Infected = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_AI_becoming_SI/AI_time_to_become_SI_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Testing_SI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = Testing.test_rate_SI
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 2
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage get tested. It is given as the product of the number of people currently in the stock and the respective fractional testing rate.
OUTFLOWS:
Main_Infection_Model.inf_end_T_SI_s1 = CONVEYOR OUTFLOW
OUTFLOW PRIORITY: 1
UNITS: person/day
Main_Infection_Model.TSI_s2_rate = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_becoming_HI/SI_time_to_become_HI_distribution_per_flow

EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 1
OUTFLOW PRIORITY: 2
UNITS: person/day
DOCUMENT: The rate of movement to the next stage of infection is represented as a material delay controlled by the fraction that is expected to move to the next stage over the avg time to move to the next stage
Main_Infection_Model.Recovery_T_SI_s1 = LEAKAGE OUTFLOW
LEAKAGE FRACTION = fraction_SI_recovering/SI_recovery_time_distribution_per_flow
EXPONENTIAL LEAKAGE
LEAK ZONE = 0% to 100%
CONVEYOR FILL = BASED ON SOURCE
INFLOW PRIORITY: 3
OUTFLOW PRIORITY: 3
UNITS: person/day
DOCUMENT: The rate at which Infected individuals at this severity stage recover. It is represented as a material delay given by the fraction of infected recovering over the avg recovery time controlling this particular outflow.
Main_Infection_Model.Total_Dead_CCI = CCI_Recent_Dead+CCI_Dead
UNITS: People
DOCUMENT: The total number of infected persons who have died from this severity category
Main_Infection_Model.Total_Dead_HI = HI_Recent_Dead+HI_Dead
UNITS: People
DOCUMENT: The total number of infected persons who have died from this severity category
Main_Infection_Model.Total_Dead_T_CCI = T_CCI_Recent_Dead+T_CCI_Dead
UNITS: People
DOCUMENT: The total number of infected persons who have died from this severity category
Main_Infection_Model.Total_Dead_T_HI = T_HI_Recent_Dead+T_HI_Dead
UNITS: People
DOCUMENT: The total number of infected persons who have died from this severity category
Main_Infection_Model.Total_Recovered_AI = AI_Recovered+AI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_CCI = CCI_Recovered+CCI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_HI = HI_Recovered+HI_Recent_Recovered
UNITS: People

DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_SI = SI_Recovered+SI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_T_AI = T_AI_Recovered+T_AI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_T_CCI = T_CCI_Recovered+T_CCI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_T_HI = T_HI_Recovered+T_HI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
Main_Infection_Model.Total_Recovered_T_SI = T_SI_Recovered+T_SI_Recent_Recovered
UNITS: People
DOCUMENT: The total number of infected persons who have recovered from this severity category
********** Main_Infection_Model.Calculations_As_fraction_of_total_infections: **********
Main_Infection_Model.fr_AI_of_Total = Total_AI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_ALL_who_have_been_CCI_of_total = (Total_Dead_CCI+Total_Recovered_CCI)//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction that has recovered or died as Critical Care Infected out of all COVID-19 infections
Main_Infection_Model.fr_ALL_who_have_been_HI_of_total = (Total_Dead_HI+Total_Recovered_HI)//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction that has recovered or died as Hospitalised Infected out of all COVID-19 infections
Main_Infection_Model.fr_ALL_who_have_been_T_CCI_of_total = (Total_Dead_T_CCI+Total_Recovered_T_CCI)//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction that has recovered or died as Tested Critical Care Infected out of all COVID-19 infections
Main_Infection_Model.fr_ALL_who_have_been_T_HI_of_total = (Total_Dead_T_HI+Total_Recovered_T_HI)//All_Cumulative_Cases

UNITS: dmnl
DOCUMENT: The fraction that has recovered or died as Tested Hospitalised Infected out of all COVID-19 infections
Main_Infection_Model.fr_CCI_of_Total = Total_CCI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_DEAD_as_CCI_of_Total = Total_Dead_CCI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has died as Critical Care Infected
Main_Infection_Model.fr_DEAD_as_HI_of_Total = Total_Dead_HI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has died as Hospitalised Infected
Main_Infection_Model.fr_DEAD_as_T_CCI_of_Total = Total_Dead_T_CCI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has died as tested Critical Care Infected
Main_Infection_Model.fr_DEAD_as_T_HI_of_Total = Total_Dead_T_HI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has died as Tested Hospitalised Infected
Main_Infection_Model.fr_DEAD_who_have_been_CCI_or_T_CCI_of_Total = fr_DEAD_as_CCI_of_Total+fr_DEAD_as_T_CCI_of_Total
UNITS: dmnl
DOCUMENT: The fraction that has died as Critical Care Infected (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.fr_DEAD_who_have_been_HI_or_T_HI_of_Total = fr_DEAD_as_HI_of_Total+fr_DEAD_as_T_HI_of_Total
UNITS: dmnl
DOCUMENT: The fraction that has died as Hospitalised Infected (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.fr_HI_of_Total = Total_HI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_REC_who_have_been_CCI_or_T_CCI_of_Total = fr_recovered_as_CCI_of_Total+fr_recovered_as_T_CCI_of_Total
UNITS: dmnl
DOCUMENT: The fraction that has recovered as Critical Care Infected (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.fr_REC_who_have_been_HI_or_T_HI_of_Total = fr_recovered_as_HI_of_Total+fr_recovered_as_T_HI_of_Total
UNITS: dmnl
DOCUMENT: The fraction that has recovered as Hospitalised Infected (tested or not tested) out of all COVID-19 infections

Main_Infection_Model.fr_recovered_as_AI_of_Total = Total_Recovered_AI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Asymptomtic Infected
Main_Infection_Model.fr_recovered_as_CCI_of_Total = Total_Recovered_CCI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Critical Care Infected
Main_Infection_Model.fr_recovered_as_HI_of_Total = Total_Recovered_HI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Hospitalised Infected
Main_Infection_Model.fr_recovered_as_SI_of_Total = Total_Recovered_SI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Symptomatic Infected
Main_Infection_Model.fr_recovered_as_T_AI_of_Total = Total_Recovered_T_AI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Tested Asymptomtic Infected
Main_Infection_Model.fr_recovered_as_T_CCI_of_Total = Total_Recovered_T_CCI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Tested Critical Care Infected
Main_Infection_Model.fr_recovered_as_T_HI_of_Total = Total_Recovered_T_HI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Tested Hospitalised Infected
Main_Infection_Model.fr_recovered_as_T_SI_of_Total = Total_Recovered_T_SI//All_Cumulative_Cases
UNITS: dmnl
DOCUMENT: The fraction of all cases that has recovered as Tested Symptomatic Infected
Main_Infection_Model.fr_SI_of_Total = Total_SI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_T_AI_of_Total = Total_T_AI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_T_CCI_of_Total = Total_T_CCI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_T_HI_of_Total = Total_T_HI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fr_T_SI_of_Total = Total_T_SI//All_Cumulative_Cases
UNITS: dmnl
Main_Infection_Model.fraction_Asymptomatic_of_Total_Infected = fr_recovered_as_AI_of_Total+fr_recovered_as_T_AI_of_Total
UNITS: dmnl

DOCUMENT: The fraction that has recovered as Asymptomatic (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.fraction_Critical_Care_of_Total_Infected = fr_ALL_who_have_been_CCI_of_total+fr_ALL_who_have_been_T_CCI_of_total
UNITS: dmnl
DOCUMENT: The fraction that has recovered or died as Critical Care Infected (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.fraction_Hospitalised_of_Total_Infected = fr_ALL_who_have_been_HI_of_total+fr_ALL_who_have_been_T_HI_of_total
UNITS: dmnl
DOCUMENT: The fraction that has recovered or died as Hospitalised Infected (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.fraction_Symptomatic_of_Total_Infected = fr_recovered_as_SI_of_Total+fr_recovered_as_T_SI_of_Total
UNITS: dmnl
DOCUMENT: The fraction that has recovered as Symptomatic (tested or not tested) out of all COVID-19 infections
Main_Infection_Model.Total_AI = AI_s2 + AI_s3 + Asymptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Asymptomatic infected at all three sub-stages
Main_Infection_Model.Total_CCI = CCI_s2 + CCI_s3 + Critical_Care_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Critical Care infected at all three sub-stages
Main_Infection_Model.Total_HI = HI_s2 + HI_s3 + Hospitalised_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Hospitalised infected at all three sub-stages
Main_Infection_Model.Total_SI = SI_s2 + SI_s3 + Symptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Symptomatic infected at all three sub-stages
Main_Infection_Model.Total_T_AI = T_AI_s2 + T_AI_s3 + Tested_Asymptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All tested Asymptomatic infected at all three sub-stages
Main_Infection_Model.Total_T_CCI = T_CCI_s2 + T_CCI_s3 + Tested_Critical_Care_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All tested Critical Care infected at all three sub-stages

Main_Infection_Model.Total_T_HI = T_HI_s2 + T_HI_s3 + Tested_Hospitalised_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All tested Hospitalised infected at all three sub-stages
Main_Infection_Model.Total_T_SI = T_SI_s2 + T_SI_s3 + Tested_Symptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All tested Symptomatic infected at all three sub-stages
********** Main_Infection_Model.Day_of_Infection_Calculations:
These calculations have been exluded from the full documentation. The all consist from the following calculation: **Persons are arrayed by "slats", positions within the conveyor for every DT. With our used ¼ DT and 45 days of Transit Time for each Conveyor, each Conveyor stock has 180 slats. Those slats are calculated from the end of the Conveyor, (person enters the Conveyor at the 180th slat, moves to 179th etc. until it leaves it from slat 1). To transform "slats" to days of infection, we have inversed the positioning and combined 4 slats to represent 1 time unit (1 day). An example of the calculation is:**
Main_Infection_Model.AI_per_day_of_infection[1] = SUM(AI[177:180])
UNITS: people
DOCUMENT: The number of Asymptomatic Infected persons, arrayed by the day of infection they are currently underway.
In this example, we take the SUM of Asymptomatic Infected at slats 177 to 180, and place them in the 1st position of the "day of infection" array. In this way, the sum of all units within those slats is now what we will get if we ask the Software to return the value of Asymptomatic Infected at day of infection = 1. The same calculation has been performed for all Conveyors and all "slats"
********** Main_Infection_Model.Flows: **********
Main_Infection_Model.Becoming_Tested_CCI = Testing_CCI_s1 + Testing_CCI_s2 + Testing_CCI_s3 + becoming_Tested_Critical_Care_Infected {SUMMING CONVERTER}
UNITS: People/Day
DOCUMENT: The number of infected people who enter daily Intensive care or are being confirmed as infected after admission.
Main_Infection_Model.Becoming_Tested_Hospitalised = Testing_HI_s1 + Testing_HI_s2 + Testing_HI_s3 + becoming_Tested_Hospitalised_Infected {SUMMING CONVERTER}
UNITS: People/Day
DOCUMENT: The number of infected people who become daily hospitalised or are being confirmed as infected after admission.

Main_Infection_Model.Testing_rates_SUM = Testing_AI_s1 + Testing_AI_s2 + Testing_AI_s3 + Testing_CCI_s1 + Testing_CCI_s2 + Testing_CCI_s3 + Testing_HI_s1 + Testing_HI_s2 + Testing_HI_s3 + Testing_SI_s1 + Testing_SI_s2 + Testing_SI_s3 {SUMMING CONVERTER}
UNITS: PErson/Day
DOCUMENT: The sum of daily testing rates in all severity categories.
Main_Infection_Model.Total_Dying = Dying_CCI_s1 + Dying_CCI_s2 + Dying_CCI_s3 + Dying_HI_s1 + Dying_HI_s2 + Dying_HI_s3 + Dying_T_CCI_s1 + Dying_T_CCI_s2 + Dying_T_CCI_s3 + Dying_T_HI_s1 + Dying_T_HI_s2 + Dying_T_HI_s3 {SUMMING CONVERTER}
UNITS: People/Day
DOCUMENT: The total number of people dying per day due to a COVID-19 infection or related complications
Main_Infection_Model.Total_Dying_Tested = Dying_T_CCI_s1 + Dying_T_CCI_s2 + Dying_T_CCI_s3 + Dying_T_HI_s1 + Dying_T_HI_s2 + Dying_T_HI_s3 {SUMMING CONVERTER}
UNITS: People/Day
DOCUMENT: The total number of Tested Infected people dying per day due to a COVID-19 infection or related complications
********** Main_Infection_Model.Fractions: **********
Main_Infection_Model.All_Cumulative_Cases(t) = All_Cumulative_Cases(t - dt) + (Daily_New_Cases) * dt
INIT Main_Infection_Model.All_Cumulative_Cases = 0
UNITS: person
DOCUMENT: All the cases ever to have been infected by covid-19. increases through the daily new cases flow
INFLOWS:
Main_Infection_Model.Daily_New_Cases = Infection_Rate+Imported_Cases
UNITS: person/day
DOCUMENT: the sum of local and imported cases of covid-19
Main_Infection_Model.All_ever_infected_as_fraction_of_the_population = All_Cumulative_Cases//NORWAY_INIT_POP
UNITS: Dmnl
DOCUMENT: The fraction of the population that has been ever infected by covid-19 is given as the ratio of all cumulative covid-19 cases and the population of norway
********** Main_Infection_Model.Sector_1: **********
Main_Infection_Model.Confirmed_Daily_New_Cases_DATA = GRAPH(TIME)

Points(119): (50,0, 0,0), (51,0, 1,0), (52,0, 0,0), (53,0, 0,0), (54,0, 0,0), (55,0, 0,0), ...
UNITS: People/Day
DOCUMENT: Daily new cases as reported by the Norwegian Health authorities. Data from "Number of reported COVID-19 cases by specimen collection date" (Norwegian Institute of Public Health - FHI, 2020). Accessed 15.06.20
Main_Infection_Model.Cumulative_Confirmed_Cases_DATA = GRAPH(TIME)
Points(119): (50,0, 0,0), (51,0, 1,0), (52,0, 1,0), (53,0, 1,0), (54,0, 1,0), (55,0, 1,0), ...
UNITS: People
DOCUMENT: Cumulative COVID-19 confirmed cases as reported by the Norwegian Health authorities. Data from "Number of reported COVID-19 cases by specimen collection date" (Norwegian Institute of Public Health - FHI, 2020). Accessed 15.06.20
Main_Infection_Model.Cumulative_Deaths_DATA = GRAPH(TIME)
Points(79): (70,00, 0,0), (71,00, 1,0), (72,00, 1,0), (73,00, 1,0), (74,00, 3,0), (75,00, 3,0), ...
UNITS: Persons
DOCUMENT: Cumulative as reported by the Norwegian Health authorities. Data from daily reports (Norwegian Institute of Public Health - FHI, 2020). Accessed 15.06.20
Main_Infection_Model.Cumulative_Intensive_Care_Admissions_DATA = GRAPH(TIME)
Points(78): (68,00, 0,0), (69,00, 3,0), (70,00, 5,0), (71,00, 6,0), (72,00, 7,0), (73,00, 8,0), ...
UNITS: people
DOCUMENT: "Number of new patients with laboratory-confirmed COVID-19 admitted to intensive care, by admission date" (FHI, 2020). Accessed 30.05.20
Main_Infection_Model.Cumulative_Total_Hospital_Admissions_DATA = GRAPH(TIME)
Points(78): (68,00, 0,0), (69,00, 6,0), (70,00, 11,0), (71,00, 14,0), (72,00, 21,0), (73,00, 29,0), ...
UNITS: People
DOCUMENT: "Number of new patients admitted to hospital with COVID-19 as main reason for admission, by admission date" (FHI, 2020). Accessed 30.05.2020
Main_Infection_Model.Currently_Hospitalised_DATA = GRAPH(TIME)
Points(84): (67,00, 0,0), (68,00, 2,0), (69,00, 8,0), (70,00, 13,0), (71,00, 23,0), (72,00, 27,0), ...
UNITS: People
DOCUMENT: Data on number of COVID-19 hospitalised cases. "Covid-19 - antall innlagte pasienter på sykehus" (Norwegian Institute of Public Health - FHI, 2020). Accessed 30.05.20
Main_Infection_Model.Currently_Intensive_DATA = GRAPH(TIME)
Points(84): (67,00, 0,0), (68,00, 0,0), (69,00, 0,0), (70,00, 0,0), (71,00, 1,0), (72,00, 4,0), ...
UNITS: People
DOCUMENT: Data on number of COVID-19 cases in intensive care. "Covid-19 - antall innlagte pasienter på sykehus" (Norwegian Institute of Public Health - FHI, 2020). Accessed 30.05.20
Main_Infection_Model.New_Deaths_DATA = GRAPH(TIME)
Points(79): (70,00, 0,0), (71,00, 1,0), (72,00, 0,0), (73,00, 0,0), (74,00, 2,0), (75,00, 0,0), ...
UNITS: Persons/Day

DOCUMENT: The number of daily deaths, as reported by the Norwegian Institute of Public Health - FHI (2020)
Main_Infection_Model.New_Hospital_Admissions_DATA = GRAPH(TIME)
Points(78): (68,00, 0,0), (69,00, 6,0), (70,00, 5,0), (71,00, 3,0), (72,00, 7,0), (73,00, 8,0), ...
UNITS: People/Day
DOCUMENT: The number of daily new hospital admissions, as reported by the Norwegian Institute of Public Health - FHI (2020)
"Number of new patients admitted to hospital with COVID-19 as main reason for admission, by admission date" (FHI, 2020). Accessed 30.05.2020
Main_Infection_Model.New_Intensive_Care_Admissions_DATA = GRAPH(TIME)
Points(78): (68,00, 0,0), (69,00, 3,0), (70,00, 2,0), (71,00, 1,0), (72,00, 1,0), (73,00, 1,0), ...
UNITS: people/Day
DOCUMENT: The number of admissions to the intensive care, as reported by the Norwegian Institute of Public Health - FHI (2020).
"Number of new patients with laboratory-confirmed COVID-19 admitted to intensive care, by admission date" (FHI, 2020). Accessed 30.05.20
Main_Infection_Model.NORWAY_INIT_POP = 5367580
UNITS: People
DOCUMENT: The Population of Norway as of February 27th 2020 (Statistisk Sentralbyrå - Statistics Norway, 2020)
Main_Infection_Model."transit_time_-_max_duration_of_infection" = 45
UNITS: days
********** Main_Infection_Model.Total_Stocks: **********
Main_Infection_Model.All_AI = AI_s2 + AI_s3 + Asymptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Infected who are currently Asymptomatic as the sum from all three stages of the Asymptomatic severity category
Main_Infection_Model.All_Asymptomatic_Infected = All_AI + All_T_AI {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All who are currently infected and Asymptomatic, both tested and non-tested.
Main_Infection_Model.All_CCI = CCI_s2 + CCI_s3 + Critical_Care_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Infected who are currently in Critical Care as the sum from all three stages of the Critical Care severity category
Main_Infection_Model.All_Critical_Care_Infected = All_CCI + All_T_CCI {SUMMING CONVERTER}
UNITS: People

DOCUMENT: All who are currently infected in Critical Care, both tested and non-tested.
Main_Infection_Model.ALL_CURRENTLY_INFECTED = All_Currently_Infected_NonTested + All_Currently_Infected_Tested {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All the individuals who are currently infected with COVID-19 infection in any of the severity categories, both tested and non-tested.
Main_Infection_Model.All_Currently_Infected_NonTested = All_AI + All_CCI + All_HI + All_SI {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All people who are currently infected but not tested. It is the sum of all currently infected Asymptomatic, Symptomatic, Hospitalised, and Critical Care stages
Main_Infection_Model.All_Currently_Infected_Tested = All_T_AI + All_T_CCI + All_T_HI + All_T_SI {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All people who are currently infected and tested. It is the sum of all currently infected and Tested Asymptomatic, Symptomatic, Hospitalised, and Critical Care stages
Main_Infection_Model.ALL_DEAD = All_Dead_NonTested + All_Dead_Tested {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All the individuals who have died due to a COVID-19 infection from any of the severity categories, both tested and non-tested.
Main_Infection_Model.All_Dead_NonTested = Total_Dead_CCI + Total_Dead_HI {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All people who have died from Covid-19 without ever being tested. It is the sum of the total (non-tested) dead after either being Hospitalised or in Critical care
Main_Infection_Model.All_Dead_Tested = Total_Dead_T_CCI + Total_Dead_T_HI {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All people who have died from Covid-19 after being tested. It is the sum of the total tested dead after either being Hospitalised or in Critical care
Main_Infection_Model.ALL_EVER_INFECTED = Cumulative_infected_NonTested + Cumulative_infected_Tested {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All the individuals who were ever infected by COVID-19 infection in any of the severity categories, both tested and non-tested.
Main_Infection_Model.All_HI = HI_s2 + HI_s3 + Hospitalised_Infected {SUMMING CONVERTER}
UNITS: People

DOCUMENT: All Infected who are currently Hospitalised as the sum from all three stages of the Hospitalised severity category
Main_Infection_Model.All_Hospitalised_Infected = All_HI + All_T_HI {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All who are currently infected and Hospitalised, both tested and non-tested.
Main_Infection_Model.ALL_RECOVERED = All_Recovered_NonTested + All_Recovered_Tested {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All who have recovered from a Covid-19 infection from any of the severity categories, both tested and non-tested.
Main_Infection_Model.All_Recovered_NonTested = Total_Recovered_AI + Total_Recovered_CCI + Total_Recovered_HI + Total_Recovered_SI {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All people who have recovered and had never been tested. It is the sum of all (non-tested) recovered Asymptomatic, Symptomatic, Hospitalised, and Critical Care stages
Main_Infection_Model.All_Recovered_Tested = Total_Recovered_T_AI + Total_Recovered_T_CCI + Total_Recovered_T_HI + Total_Recovered_T_SI {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All people who have recovered and had been tested. It is the sum of all Tested recovered Asymptomatic, Symptomatic, Hospitalised, and Critical Care stages
Main_Infection_Model.All_SI = SI_s2 + SI_s3 + Symptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Infected who are currently Symptomatic as the sum from all three stages of the Symptomatic severity category
Main_Infection_Model.All_Symptomatic_Infected = All_SI + All_T_SI {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All who are currently infected and Symptomatic, both tested and non-tested.
Main_Infection_Model.All_T_AI = T_AI_s2 + T_AI_s3 + Tested_Asymptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Tested Infected who are currently Asymptomatic as the sum from all three stages of the Asymptomatic severity category
Main_Infection_Model.All_T_CCI = T_CCI_s2 + T_CCI_s3 + Tested_Critical_Care_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Tested Infected who are currently in Critical Care as the sum from all three stages of the Critical Care severity category
Main_Infection_Model.All_T_HI = T_HI_s2 + T_HI_s3 + Tested_Hospitalised_Infected {SUMMING CONVERTER}

UNITS: People
DOCUMENT: All Tested Infected who are currently Hospitalised as the sum from all three stages of the Hospitalised severity category
Main_Infection_Model.All_T_SI = T_SI_s2 + T_SI_s3 + Tested_Symptomatic_Infected {SUMMING CONVERTER}
UNITS: People
DOCUMENT: All Tested Infected who are currently Symptomatic as the sum from all three stages of the Symptomatic severity category
Main_Infection_Model.Cumulative_infected_NonTested = All_Currently_Infected_NonTested + All_Dead_NonTested + All_Recovered_NonTested {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All the people who were ever Infected and not tested Tested. It is the sum of all the people who are currently infected, who have recovered, and who have died without ever being tested.
Main_Infection_Model.Cumulative_infected_Tested = All_Currently_Infected_Tested + All_Dead_Tested + All_Recovered_Tested {SUMMING CONVERTER}
UNITS: people
DOCUMENT: All the people who were ever Infected and Tested. It is the sum of all the people who are currently infected, who have recovered, and who have died after being tested.
{ The model has 307 (2091) variables (array expansion in parens).
In this module and 0 additional modules with 6 sectors.
Stocks: 51 (51) Flows: 110 (110) Converters: 146 (1930)
Constants: 56 (56) Equations: 200 (1984) Graphicals: 11 (11)
There are also 141 expanded macro variables.