university of groningen / faculty of mathematics and natural sciences / artificial intelligence

---

# Simulating Social Interaction in Times of COVID Restrictions

Oscar de Vries

March 2022

Master Thesis
Artificial Intelligence (Multi-Agent Systems)
University of Groningen, The Netherlands

Internal Supervisor:
Prof. Dr. L.C. Verbrugge (Artificial Intelligence, University of Groningen)

External Supervisor:
Dr. W. Jager (University College, University of Groningen)

# FOREWORD

The research in this thesis was conducted under special circumstances. The university has been closed for most of the time due to the COVID pandemic. Hence, working at the university facilities was not possible and the majority of the process had to be done at home. Also, most of the meetings for discussing the process were done online. Even though these circumstances were sometimes difficult in terms of motivation and concentration, they were not insurmountable. One of the reasons is the support and inspiration from my supervisors, which has helped me tremendously. Hence, I want to express my gratitude to my supervisors for their guidance during this project.

Firstly, I would like to thank Rineke Verbrugge for her supervision and support. Not only has Rineke supervised me during the master project, but she has also supervised my bachelor project and has been a teacher for many courses in the curriculum. Thank you for inspiring me and for supplying me with ideas when I got stuck, which has helped a lot with academic research and writing. Also, I'm very grateful that Rineke introduced me to my second supervisor, Wander Jager, who turned out to be a great match.

Secondly, therefore, I would like to thank Wander, for his supervision and support during this project. Thank you for introducing me to the HUMAT framework and helping me integrate my ideas with it. I am also very grateful that you allowed me to work in your office during the project when the pandemic allowed it. I enjoyed our talks about agent-based modelling, music and many other subjects.

# ABSTRACT

Many agree that COVID measures are necessary for reducing pressure on our health system. However, they have dramatic social and economic downsides. One of the measures in the Netherlands is the *visitors measure* (bezoekersmaatregel), with which the government advises receiving no more than a maximum number of visitors per day. The intended effect is social distancing, which directly opposes the need for many to experience social contact. For young adults, especially those living alone, social contact is crucial for making friends, building a network and general well-being. Many young adults experience mental health issues resulting from a lack of social contact. Consequently, support and compliance for the visitors measure have been decreasing in the period March 2020–February 2022.

This thesis presents an agent-based model developed to explore this case. More specifically, such a model is used to study the interaction between the need to experience social contact and the support base for the visitors measure. Agent-based modelling can be used to study the emergence of macro-level behaviour of a population as a result of changes in micro-level characteristics in individuals, and to study changes in individual behaviour resulting from changes to the environment. In our case, we limit the agents allowed visitors per day, to study the effect of this measure on the amount of contact and the support for the visitors measure.

The decision-making mechanism of the agents is mainly structured by the HUMAT integrated framework: a cognitive framework based on social scientific theory in which agents determine their behaviour on the basis of satisfying different needs. Potentially, some of their needs are conflicting: agents, on the one hand, have the experiential need to experience social interaction with others, but on the other hand have the values need to contribute to general health by following the visitors measure, thereby refraining from social interaction. Moreover, agents have an opinion on the visitors measure, which represents their support. Agents have the social need to belong to their social group, with regards to these opinions. Interaction between agents leads to opinion-influencing effects. Data from RIVM (National Institute for Public Health and the Environment) surveys on the support for the visitors measure is used to initialize the opinions of the agents, such that the opinions of the agent population resemble those of the Dutch population.

Simulations of the model are used to study the change in efficacy and support for different policies, varying the strength of the visitors measure. Experiments are performed to study behaviour in both single HUMAT populations, using the RIVM data for initialization of opinions, and in more general patterns, considering aggregated behaviour of multiple HUMAT populations.

Results show that decreasing the allowed number of visitors leads to a lower total amount of contact, but also to a lower support base for the measure. Interestingly, for the strictest visitors measures, with the fewest allowed daily visitors, the support base is increasingly lower, while the intended effect on lowering the total amount of contact is relatively little.

We conclude that there exists a trade-off between efficacy and support for the visitors measure. Stricter measures are initially effective in reducing numbers of contact, but the effect stagnates, while support does continue to decrease. A sweet spot may exist in which the policy is effective while maintaining general acceptance.

# CONTENTS

# 1 | Introduction

At the moment of writing this thesis, the world is experiencing the COVID-19 pandemic, the biggest public health threat since the second world war (Sample, December 2020). In order to battle the spreading of the coronavirus, governments are taking fierce measures to prevent humans from coming into contact with each other, leading to a lower number of infections. Lockdown measures such as curfew and visitor limitations heavily restrict the freedom of citizens. The main goal of these measures is to reduce pressure on healthcare, in hospitals and nursing homes, such that healthcare remains accessible to those in need.

## 1.1 Problem description

Although many agree social-distancing measures are necessary in order to prevent the spreading of the virus, unfortunately, they have dramatic social and economic downsides. For many human beings, the intended effect of avoiding contact directly opposes their need to experience social contact. Having the focus mainly on healthcare and protecting people at risk comes at the expense of other factors. A result of prolonging the measures is that it leads to a growing impact on mental health. Leaving the house and coming into contact with friends leads to a positive effect on mental well-being, due to more experienced variation (Gloster et al., 2021, p. 15). Hence, curtailing this possibility could have the opposite effect.

One of the groups for which the measures are difficult is young adults. According to Lifelines research, in February 2021 the Northern-Dutch population graded the quality of their life with a 6.9 on average, whereas during the summer period in 2020 this was a 7.7. For young adults, this grade has dropped to a 6.0, an all-time low during the crisis (Lifelines, February 2021). Among other age groups, young adults mostly long for social contact, making friends and building their network.[1] With study activities being mostly online and other forms of contact such as sports and associations not being possible, this group experiences problems such as stress, depression, loneliness and concentration problems. On top of that, many young adults are losing their jobs and are unable to find work or internships. The uncertainty that the pandemic brings with respect to their future also contributes negatively to their mental health. Moreover, as many students live in small rooms and dorms, with typically no garden or balcony, curfew is extra tough. This holds especially for young adults living on their own, with no roommates and the reduced possibilities for social contact. The feeling of loneliness and isolation are substantially stronger in individuals living alone, with this effect being the strongest in the ages between 18 and 30 (Mc Intyre et al., 2021). In the

[1] Age groups 5-9, 10-19 and 20-29 have the highest mean number of contacts outside of COVID times, according to Backer et al. (2020, p. 4).

same small room, they have to sleep, study, work, eat and spend their spare time. Having the obligation to remain in the same room increases mental health problems even further.

Research done by 113 suicide prevention has shown that the suicide rate for the age group up to 30 years has increased by 15% in 2021 (CANS, January 2022). Though it's not certain, it is highly likely that the corona measures have influenced this increase. Many of the measures directly affect domains that are very important to young adults in this age group, such as having contacts with others, forming friendships, discovering the world and future perspective. Moreover, the research by 113 states that the increase in suicide is only one tip of the iceberg. Young adults have reported twice as many mental complaints than other age groups during lockdowns, such as increased tiredness, gloom and loss of perspective. A few months after the lockdowns have ended, they still report one and a half times as many mental complaints. Recovering from these complaints take time, and for some young adults, problems start stacking up if the next lockdown begins before they had the chance to recover.

As a consequence of these complaints, the support for the measures is decreasing. An increasing amount of young adults choose not to follow measures in favour of satisfying their needs for social contact, for example by meeting up with more than the allowed number of visitors per day.

In this project, we aim to model the interaction between the need to experience social contact and the support base for the corona measures. Specifically, we focus on the *visitors measure*, which is an advice to receive no more than a maximum number of visitors per day. We aim to create a multi-agent simulation in which the dynamics between the support for the Dutch COVID visitors measure and the need for social contact can be studied. The agents represent a group of young adults, who live on their own and have different conflicting needs. On the one hand they have the need to experience social contact and meet friends, but on the other they want to adhere to the visitors measure, which limits the allowed number of visitors per day. Using the model, we hope to explore how the efficacy of and the support base for this measure changes over time. Survey data from the Dutch National Institute for Public Health and the Environment (RIVM) on the support for these measures can be used to initialize the agent population with, such that the distribution of the agents' opinions resembles the opinions of the participants. Interestingly, agent-based simulations can play a crucial role in policy-making during a pandemic, as they have the advantage of studying policy without dealing with the dangers that the pandemic brings. Instead, persons are represented by autonomously acting digital agents, acting according to their mental state and needs (Wooldridge, 2009).

## 1.2 Research Questions

Given the described problem, there are two broad research questions that arise. Firstly, we wonder whether it is possible to create a simulation, in which we capture the main elements of the interaction between the support for the Dutch COVID visitors measure and the need for social contact in an agent-based model. Secondly, we want to know what we could learn from such a model.

1. *Can we create an agent-based model in which the interaction between the support for the Dutch COVID visitors measure and the need for social contact can be explored?*

(a) *Is the HUMAT framework (Antosz et al., 2019) a suitable cognitive framework to model different agent needs and decision making for this case?*

(b) *To which extent can this model realistically capture the dynamics in this interaction?*

(c) *Is the data from RIVM surveys*[2] *sufficient to initialize the HUMATs' opinions with?*

2. *What can an agent-based model in which the interaction between the support for the Dutch COVID visitors measure and the need for social contact is modelled teach us?*

   (a) *How does the support for the visitors measure change as a result of the strictness of the measure?*

   (b) *How does the amount of social interaction change as a result of the strictness of the visitors measure?*

## 1.3 Scientific Relevance for Artificial Intelligence

The social relevance of this project comes from the fact that models, such as the one proposed, help with better understanding the complex dynamics that play a role within the interaction between mental health and COVID measures. Model results could then provide insights with regards to the most suitable policy, taking into account both physical health (by COVID-measures, limiting the spread of the virus) and mental health (by fine-tuning the same measures, limiting mental health dissatisfaction). Moreover, the model could help with understanding the societal factors that play a role in human decision making with regards to adhering to COVID measures.

On the other hand, applying ABM to specific cases, such as this topic, will contribute to the field of ABM and AI as a whole. ABM are relatively easy to understand, as they are mostly visual and one does not need to be a programmer to see the effects. This benefits the use of ABM for a better understanding of such processes in society. Moreover, ABM are always abstractions of real-life phenomena. By parameterizing the model using empirical data, we can learn which aspects are and which aren't important to include in such abstractions. Also, the use of theoretically grounded ABM is a relatively new development. This research contributes to the use of integrating a cognitive framework into ABM.

## 1.4 Thesis structure

The structure of this thesis is as follows: Chapter 2 describes the theoretical background and the foundation on which the model is built, concerning the field of agent-based modelling and its development from simple models to dynamical integrated models, theory on individual decision-making making and social influence and the HUMAT framework. Chapter 3 presents the model that is developed for this thesis, describing the implementation of the different algorithmic steps and model choices. In Chapter 4, a number of experiments that were performed with the model are discussed, along with their results. Finally, in Chapter 5, the results are interpreted and the research questions are discussed, followed by some suggestions and directions for future work and an overall conclusion.

[2] see https://www.rivm.nl/gedragsonderzoek/maatregelen-welbevinden/draagvlak

# 2 | Theoretical Background

This chapter discusses the theoretical background on which the model is built. It describes the foundations for the model, specifically discussing the field of agent-based modelling and its development from relatively simple models with simple rules to dynamical integrated models and social simulations. Moreover, some theory on individual decision making, social influence and models concerning social influence is reviewed. Furthermore, the architecture to which the model is mainly applied - the HUMAT framework - is discussed. This chapter aims to lay the foundation for the model, which will be discussed in Chapter 3.

## 2.1 Agent-based modelling

Agent-based modelling (ABM) concerns the field researching computational models that simulate an environment in which computational elements, also known as *agents*, can interact with other agents and the environment. In these types of models, one of the goals researchers have is to investigate the effects of a complex system at the macro-level emerging from the behaviour of individual computational agents at the micro-level (Gilbert, 1995). Simultaneously, complexity at the macro-level can influence processes at the micro-level, a process known as downward causation (Campbell, 1974), for instance, where a change at the level of individuals is triggered by changes in the environment. Studying these phenomena in agent-based simulations can lead to a better understanding of social processes (Epstein, 1999). The process of emergence is also known as *self-organization*. Increasing numbers of complex phenomena are conceived as self-organizing networks, in which groups of interacting agents evolve to complex, intelligent and adaptive systems. Consequently, this conception allows researchers to address some of the most fundamental issues involving actions, intentions and environments (Heylighen, 2011).

Self-organization is visible in many real-life phenomena, hence is studied broadly within ABM. In this type of model, the design is mostly aimed at the macro-levels of the simulation, such that the agents do not necessarily have to be the most intelligent. Here it suffices to design agents with the level of complexity needed for showing the studied emergent behaviour. Hence, these simulations typically involve large numbers of relatively uniform agents, with rather simple rules. Agent simulations are applied to many different domains, such as social and ecological sciences. Examples include simulations of the environment, such as dispersal of seeds (Kubo et al., 1996) and habitat destruction (Bascompte & Sole, 1996) and simulations regarding animals, such as interaction and selection between competitive species of organisms (Johnson & Seinen, 2002; Szabó & Czárán, 2001), fish school shapes and transitions (Hemelrijk & Hildenbrandt, 2008; Tunstrom et al., 2013), predator and prey-escape strategies

(Nishimura, 2002; Parrish, 1993; Zheng et al., 2005; Olberg et al., 2000).

Several sub-fields model simulations of human behaviour and the emergent phenomena. *Social simulations* primarily focus on social processes in humans, studying how individual human behaviour leads to changes in networks and communities and how individuals respond to changes in an environment. In this type of simulation, human beings are represented by agents, interacting within networks or environments. Some group processes are impossible to reproduce in laboratory settings, due to large time requirements and the necessary space. By means of computer simulations, AMBs can provide experimental control over situations that would not fit in a laboratory. Moreover, they offer the ability to repeat simulations many times without the costs normally needed for running experiments. Hence, these models are very suitable for different objectives. One objective is that these models help with understanding social phenomena. They can for instance illustrate that certain behaviour is shown as the result of simple rules. Moreover, these models can also be used for prediction, by simulating how a society responds to a given problem or policy (such as our case: the response of a network to the policy of introducing different COVID-measures). Furthermore, social simulations may be used for testing and verifying assumptions and also for the formulation of hypotheses (Gilbert & Troitzsch, 2005).

Some other instances of human-centred ABM include Grow et al. (2017), in which status beliefs are studied. A network is modelled with a hierarchy of status, investigating network properties and opinion dynamics as a result of individuals preferring changing their opinion towards individuals with higher status. Prandi & Primiero (2020) investigate the spread of misinformation during a pandemic: simulating information transmission with different levels of trust, mistrust and distrust operations by the epistemic characterization of paranoid, sceptical and standard agents, the authors study the diffusion of (mis)information and the resulting behaviour change. Moreover, the authors explore the spread of the COVID-19 disease with different protection and distancing measures in the resulting networks, such that some individuals are less inclined to follow measures as a result of misinformation. More simulations investigating the spread of infectious diseases in different domains include Harvey et al. (2007) and Ghaffarzadegan (2021).

### 2.1.1 ABM development

The first ABMs already showed the potential of the methodology. Researchers recognized the capacity of ABMs to illustrate how certain fascinating societal and group phenomena are generated from simple individual tendencies and that they could be used to further explore these social-driven processes. As a consequence, many scientists were inspired to explore dynamical processes in ABM, such as diffusion of ideas and misinformation, opinion dynamics and other social practices (Jager, 2021).

A classic example is Schelling's model of segregation, dating from 1971. In this well-known model, a neighbourhood is simulated, with agents living on entries of a grid. Each agent is either of type A or type B and is placed randomly on the grid, while some of the entries remain open. The agents were given simple preference rules: Agents are in the centre of a 3x3 grid and have 8 adjacent neighbours. They are initialized with a threshold for the minimal proportion of neighbours that are of their type. If the actual proportion is lower than this threshold, agents move randomly to one of the open entries.[1] Iteration of the experiment illustrated that initializing individuals with certain preference values for the threshold would lead to segregation of the full neighbourhood (Schelling, 1971).

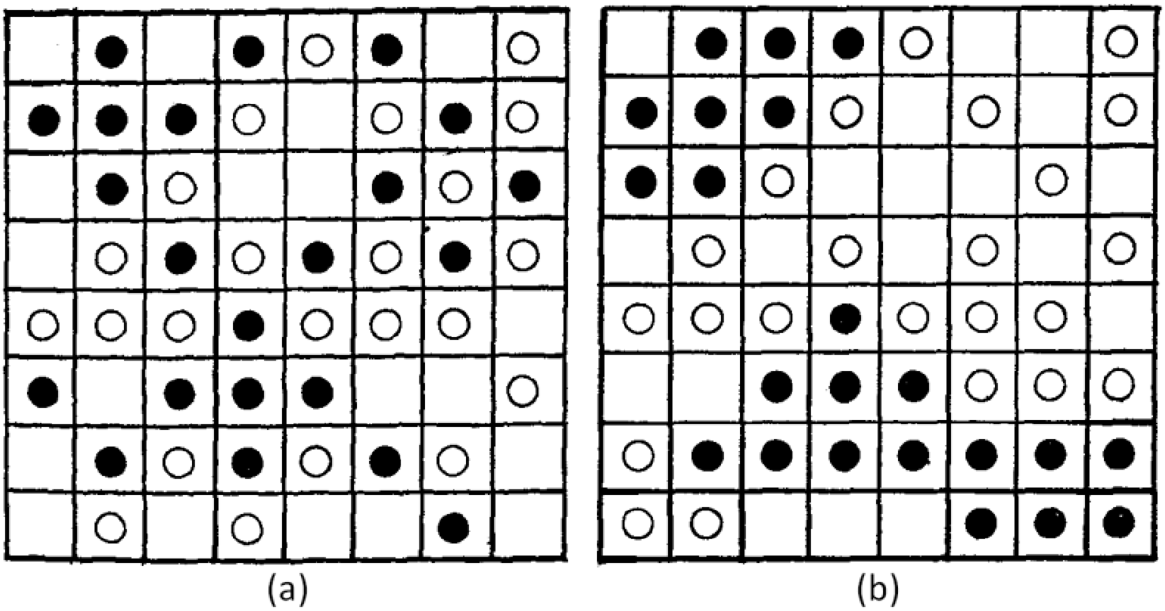



Figure 2.1: (a) shows the initial (random) distribution of agents. (b) shows the stabilized model: a neighbourhood with a segregated pattern (Schelling, 1974).

The power of Schelling's model is that it could show that a simple preference rule would lead to interesting group behaviour. However, as computation and the development of ABMs was traditionally done by computer scientists (in contrast to social scientists), the underlying assumptions on individual behaviour were often poorly grounded in behavioural theory and data. Schelling's preference rule for agents (to move randomly to an open grid entry if the proportion of neighbours of an agent's type is insufficient) does not typically reflect one's motive to move. Flache et al. (2017) argue that, even for the modellers themselves, such rules are unrealistic and that the outcomes are obvious and limited in usefulness. Hence, human behaviour should be represented in a sufficiently realistic manner in order for ABMs to be useful (Jager, 2021, p. 133).

Despite the theoretical limitations of early ABMs such as Schelling's model, the used methodology has inspired many researchers to apply a similar approach to explore behavioural dynamics, better grounded in theory. Ernst (1998) was one of the first to implement behavioural theory in an ABM, in which he models a simulation of resource dilemma, represented in a socio-ecological system of fishery (the "Fishing Conflict Game"). The agents possess ecological knowledge about the resource (a replenishable fish stock, based on an ecological model) and knowledge about the ecological knowledge, intentions and motives

[1] For example, an agent of type A could have a threshold of 50%, meaning they prefer to have at least half of the neighbours of type A. If they would have 2 neighbours of type A and 3 neighbours of type B, they would move to a random free location on the grid. With 3 neighbours of type A and 3 of type B, the agents would remain stationary.

of the other agents, as well as knowledge concerning the actions they can engage in (with regards to their motive). In the model, the agents represented a heterogeneous population, where agents differ in their prime motive: The agents' prototypical motive could be

1. to maximize individual gain,
2. to maximize overall resource outcome, or
3. to minimize the differences between participating agents.

Interestingly, the results of the simulations illustrated many similarities between the behaviour of the artificial population of agents and the behaviour of real people interacting on the basis of the ecological model. Real people could play the Fishing Conflict Game with artificial agents, without identifying them as being such. Consequently, this indicated that the human behaviour was represented in a sufficiently realistic manner, thereby correctly illustrating the variety of behaviours induced from real-life experimentation. Ernst was one of the pioneers to use behavioural theory in an ABM to investigate an environmental issue. The approach has demonstrated the suitability of ABM to integrate social scientific principles in models of ecological systems. Hence, the approach was used to study many different environmental issues using ABMs. Some instances of environmental issues include: social-ecological systems such as fishery, land management and water use, transportation, home energy use and consumer behaviour (For more elaborate descriptions of ABMs regarding different environmental issues, see Jager (2021, pp. 134 - 136)).

Over the last years, the number of models addressing environmental issues has increased, relevant to increasing awareness of climate change. Social innovations, such as the change towards a sustainable lifestyle, are very suitable to explore using social simulation. Kangur et al. (2017) use an integrated behavioural model to investigate the transition from fuel cars to electric cars, exploring the interaction between policies and consumer behaviour over a number of decades. In the model, an agent architecture designed to address customer needs and decision strategies is parametrized using respondent data. Experiments indicate that a long-lasting implementation of a combination of monetary, structural and information measures is necessary to ensure effective policy. This is an example of research that implemented an integrated model, involving the CONSUMAT (Jager, 2000), a theoretical framework that integrates consumer needs with decision strategies.

In contrast to earlier ABMs, newer models that are developed integrate more theory on behavioural processes, with the micro rules increasing by being grounded in social scientific theory. For instance, newer models might not only include behavioural theory on decision making but also combine this with a cognitive component such as the needs underlying the decision making or with theory on social interactions. A general trend within ABM is that agents have become more intelligent, such that agent design incorporates theories from psychology, sociology and behavioural studies, leading to more complex simulations. This shines a light on one of the key challenges of the field: determining the suitable level of theory that should be integrated into a model. It seems that many theoretical ideas are relevant in capturing the full complexity of human behaviour. However, adding too many theoretical components has its downside, as it may lead to models with behaviour too difficult to understand. Consequently, the outcomes are harder to validate, leading to lower applicability. Hence, there exists a trade-off between simplicity and completeness and a suitable balance should be found between them, which ultimately depends on the intended use of a model (Jager, 2021, p. 136).

We have discussed the development of the field of ABM and have seen that many studies primarily explore macro-level effects as a result of individual behaviour. Another type of research goal within ABM is centred around the design of particular agents: in contrast to macro-level effects in the self-organizational models, the behaviour of individual intelligent agents is more prominent. Here, the goal is to design an agent in a particular way and test its behaviour by means of a simulation, in order to circumvent problems and errors. Consequently, the use of a resulting physical or actual agent in a particular application can be empirically validated. For example, an ABM simulation can be used to validate behaviour for a physical robot (Bellifemine et al., 2007).

Many types of ABM's are available and their use has evolved into various communities and sub-fields, for instance, modelling human behaviour and studying emergent phenomena. One can even speak of the development of a new dynamical social science, or as Epstein calls it, *generative social science* (Epstein, 2006), in which agent-based models are new tools for empirical research. Due to the diversity of ABMs, the exact semantics of the different terms lead to confusion. Frequently, the term 'agent' is the only thing different communities applying ABM have in common. Moreover, not only does the inconsistent use of terms within ABM causes confusion, but also the whole field is confused with related domains, such as *Multi-agent systems* (MAS) and *Individual-based modelling* (IBM) (Niazi & Hussain, 2011). Between ABM and MAS there remains discussion on which of the domains is a sub-domain of the other or whether we can even speak of sub-domains at all. Moreover, many authors use the terms interchangeably, contributing to the confusion. However, we will treat them as two different domains with overlapping content and will elaborate on some of the perceived differences in the remainder of this section. Also, some of the terms and key differences relating to ABM will be discussed.

### 2.1.2 Agents

Agents are the main elements of an ABM and can represent many different entities, such as human beings, animals, plants, bacteria and many others. Agents can be defined to have two main capabilities. Firstly, agents are capable of *acting autonomously* to at least some extent. That is, they make their own decisions regarding acting in correspondence with their designed objective. Secondly, agents are capable of interacting with their environment, or with other agents, engaging in social activities such as cooperation, coordination and negotiation (Wooldridge, 2009). Other properties ascribed to agents include *reactivity*, concerning the responses to changes in an agent's environment and *pro-activity*, the ability of an agent to take initiative with respect to its goals (Wooldridge & Jennings, 1995). Depending on the specific domain, agents can range from having simple, not very intelligent behaviour to behaving intelligently.

In the field of artificial intelligence, more complex human-like concepts can be described to agents, in which their behaviour is determined by rules and their private mental state, which includes concepts such as beliefs, decisions, capabilities and obligations (Shoham, 1993).

### 2.1.3 Multi-Agent systems

A field related to agent-based modelling is that of Multi-agent systems (MAS). MAS originates in the field of Artificial Intelligence, with more specific influences by the components of logic, computer science and cognitive science. Similar to the definition of ABM, MAS are systems composed of multiple interacting computing elements (agents). Essential here, is that the system contains *multiple* agents (Wooldridge, 2009). As mentioned before, due to the broad range of applications of the field and the high level of overlap, ABM and MAS are sometimes confused. ABM usually focuses on the emergent phenomena of a simulation, making the complexity of the agents less important. In contrast, MAS typically involve the more complex designs of agents, with the goal of solving or studying a practical problem. The agent design can for instance be used to validate the underlying assumptions made in a model, such that if the simulation shows the expected outcome, the design of the agent is validated, and vice versa. MAS is most useful for problems where multiple perspectives are beneficial, because for example a single point of view is insufficient, or central control is lacking. Individual agents with different decision-making interact in a shared environment, with conflicting or shared goals. Instances of research that can be investigated with MAS are competition or cooperation between agents or robots.

Howorth (2020) distinguishes the two terms by defining MAS as more directed towards solving a particular real-life problem or task, in which multiple agents cooperate in order to solve the task. As the task is typically unsolvable by a single agent, the agents aim to find a set of behaviours in order to find the solution. In contrast, ABM is more directed towards exploring how a system may respond as a result of individual agents obeying simple rules. Here, the main aim is to gain insights into the collective behaviour of agents, rather than finding a solution to a particular problem or task.

The model in this thesis investigates the interaction between mental health and COVID-measures, studying the emergence of illegal behaviour by showing how decreasing mental health can lead to actions contrary to behaviour imposed by the COVID-measures. Comparing the model to both ABM and MAS, it can be observed that the model contains properties of both: As the main interest of this model is the dynamics in the support base of the COVID-measure regarding visitors (Dutch: bezoekersregeling) in Dutch citizens, this model focuses on an emergent phenomenon (namely, how will a network of agents respond to rules impeding the satisfaction of their needs), thereby relating the model to ABM. However, as Section 2.4 will illustrate, the agents are designed using a cognitive framework, in which their decision process is determined by their mental states. This makes the agents quite complex, as agents may alter their needs in order to remain satisfied. A relation to MAS would be that the systems aim to find the collective set of agent behaviours to solve the problem of keeping all agents satisfied in their needs.

## 2.2 Individual decision making

Since our model aims to explore human behaviour given certain restrictions, it is necessary to consider which factors play a role in the choices individuals make. In this section, different aspects that play a role in individual decision making are discussed. Specifically, the theory of *satisficing* as the basis for decision making by Herbert Simon is discussed and contrasted to classical economical models, in which *maximizing expected utility* formed the basis.

Research by Simon (1955, 1956) states that the characterization of rational choice has been a central concern in the theory of decision making, but that there are serious doubts about how it had been conceptualized until then. With regards to rational choice, economic theory tends to assume that the behaviour of individuals is aimed at maximizing expected utility. Typically, in these theories, humans are assumed to make decisions from a finite set of alternatives. A choice follows from comparing alternatives using a **utility function**, which is a function U: $X \rightarrow R$ such that $x \succ y$ if and only if $U(x) > U(y)$. This means that alternative $x$ is strictly preferred over alternative $y$ if and only if the utility of $x$ is higher than the utility of $y$. Moreover, the utility of an alternative $U(x)$ is then typically weighted by the *expectation* of that alternative, which is the probability $p_x$ that the alternative occurs. The result is the **expected utility** of an alternative: $EU(x) = p_x * U(x)$. The resulting behaviour is then the alternative (or set of alternatives in the case of a tie) that has the maximum expected utility and therefore is preferred over all other alternatives (Varian, 1992).

One of the main issues is that the use of such a function for decision making requires strong assumptions: In order to apply the utility function, one has to assume a complete, reflexive and transitive preference order on a set of alternatives, respectively such that each alternative can be compared to itself and other alternatives in the set (i.e., a preference relation exists), each outcome is related to itself and there always exists a most preferred outcome.[2] With respect to human decision making, this assumption is unrealistic: In reality, humans do not have such a clearly defined set of alternatives and preference relations between alternatives, and even if they did, mental costs are too high and time is too limited to determine the most preferred alternative in a realistic situation. Another issue comes from the way that expected utility is determined for a single alternative. Given a behavioural alternative, determining its expected utility includes multiplying the utility with the probability the alternative will result in that particular outcome. These probabilities are typically not available for humans, nor would they have the cognitive means to calculate with them.

Even though the expected utility theory might sound appealing for explaining human behaviour, in practice human adaptiveness falls short of the ideal, due to the complexity of the choice mechanisms. According to Simon, rational choice is bounded by two main components: the human mind and the fundamental structural characteristics of the environment. Maximizing expected utility in rational choice requires a level of obtaining information and performing computations that is too complex for human beings: The environment is too limited with regards to information availability and even if it were available, human cognition would be too limited to process this information (Newell et al., 2007). Moreover, the theory of rational choice based on expected utility postulates a well-defined environment, in which humans have knowledge regarding all possible behavioural alternatives and their consequences, as well as possess time and cognitive means to find the most optimal choice. However, real-world situations are typically poorly-defined, making a utility function impossible to apply. One underlying problem comes from the fact that humans do not know much about behavioural possibilities in advance. Consequently, there is no optimal method for deciding to stop considering alternatives. Moreover, humans lack the ability to know

[2] If the preference order on a set of outcomes is not transitive, there could exist cycles of preference in the set such that there is no clear preferred alternative

about the expected pay-off of the different behavioural alternatives. Furthermore, given the constraint of time and the presence of different goals, a consistency requirement is introduced, such that time that is consumed for one goal limits the time for the other goals. Therefore, in reality, humans often approach tasks using approximate methods, in which the search for further information necessary for an optimal choice is not pursued. Rather, humans act towards goals, in which they take into account information available to them. As a consequence, Simon states that the rational choice of individuals is not generally aimed at maximizing expected utility, but can be better explained by being aimed at satisfying needs (which Simon calls *satisficing*) available to them in a given situation.

For our case, the goals available to humans could represent satisfying the need for physical contact, as well as satisfying the need for following the visitors measure. A priority mechanism could be that an individual persists in searching for the behaviour that satisfies the particular need that first reaches a threshold for initiating certain behaviour. However, this would only hold for independent needs. In our case, the needs are in a trade-off, where behaviour satisfying the need for physical contact almost directly opposes behaviour satisfying the need to follow the visitors measure.[3]

Simon concludes that individuals don't have the sense nor wits to discover optimal behaviour, but that they are more directed towards satisfying needs. Even though multiple goals could be conflicting and efficient behaviour taking into account all needs is possible, in general individuals typically allocate time for behaviour aimed at satisfying single needs, without introducing coordination problems with regards to a general 'utility function'. Moreover, the psychological environment of an organism is usually structured such that only certain information is available and a central cognitive mechanism that would take into account all information is lacking. Consequently, the available information is pointing towards single needs, making a potential most efficient behavioural choice regarding all needs unavailable.

The analysis by Simon criticizes the basis for rational decision making postulated by economical theory. His alternative approach is more closely related to psychological theories of perception and cognition. It points towards a theory in which satisfying different needs is the basis for decision making. Gigerenzer et al. (1999) agree with Simon's critiques towards economical theory and state that human decision making should be built on what we know about mental capacities rather than on fictitious competencies. In many real-world situations, optimal strategies are unknown or unknowable, since our rationality is bounded. There is no optimal method for going over all alternative choices and determining the expected utility for each of them. Instead, Simon's concept of satisficing needs, in which a choice is made with limited time and limited knowledge, seems a more sufficient heuristic for decision making.

These findings support the justification for the use of the HUMAT framework, which is the cognitive framework in our model (discussed in Section 2.4). In this framework, realistic psychological mechanisms and rules are implemented by having the agents determine their behaviour and decision making based on the satisfaction of different needs and phenomena such as cognitive dissonance. Moreover, the framework includes theory about networks and communication between agents and the social influence that is involved, which will be the

[3] The needs are not in complete opposition, since the visitors measure allows for a number of contacts per day.

topic of the next section.

## 2.3 Social influence

The model in this thesis primarily explores the effect on mental health due to the lack of interaction between individuals as a result of visitor restrictions. The emergence of illegal group meetings concerning COVID-measures and the changes in support for these measures, as a result, are investigated. When individuals do interact, psychological processes of social influence take place, which in turn will affect the choices the individuals make. This section reviews some benchmark literature on social influence and models of social influence.

Cialdini & Goldstein (2004) review developments in social influence literature. The authors illustrate principal processes underlying a target's susceptibility to outside influences and study the social influence of different psychological phenomena, primarily focusing on compliance and conformity. The review emphasizes how certain goals for human functioning interact with external forces and shows the effect of social influence processes which are subtle, indirect and outside of awareness. Three of the core motivations to human functioning are:

1. Targets are motivated to form accurate perceptions of reality and react accordingly,
2. to develop and preserve meaningful social relationships, and
3. to maintain a favourable self-concept.

In the light of compliance and conformity, these fundamental goals lead to humans feeling urged to respond in the desired way: Firstly, the goal of accuracy (1) entails that humans are motivated to achieve their goals in the most effective and rewarding manner possible, which demands an accurate perception of reality.

Secondly, the goal of affiliation (2), states that human beings are fundamentally motivated to create and maintain meaningful social relationships. We use approval and liking cues for this purpose (affiliation-oriented goals), as well as abiding norms of social exchange such as reciprocity.

Thirdly, the goal of maintaining a positive self-concept (3) entails humans have a strong tendency to enhance self-concepts, by behaving consistently with their actions, statements, commitments, beliefs and self-ascribed traits. The authors mainly emphasize the interaction between these three goals and external forces to illustrate social influence processes.

For this thesis, mainly the goal of affiliation is of interest. In order to adequately understand and effectively respond to social situations, individuals tend to look to social norms to guide their behaviour. Here two types of norms are distinguished: On the one hand, there are *injunctive norms*, which inform humans about what is typically approved or disapproved. In the light of affiliation, humans believe that if they engage in behaviour approved by others, they are more likely to gain approval from others. On the other hand, *descriptive norms* are norms informing humans about what is typically done. Both the degree to which each norm is focal, as well as the extent to which different types of norms are in alignment determine the impact on behaviour.

In addition to external norms, also *personal norms* influence individuals in their behaviour. The extent of the influence of personal norms is determined by the attention an individual has on itself in comparison to external stimuli (Kallgren et al., 2000). Depending on the salience of injunctive, descriptive and personal norms, one's behaviour is influenced only when normative information is highlighted in consciousness accordingly.

Cialdini & Goldstein illustrate how these different norms socially influence human beings. In our model, these norms can be linked to different needs of the agents: Personal norms can be linked to values needs, where an agent has the needs to act according to its norms to satisfy its values needs. Hence, it feels the need to follow the visitors measure. Moreover, an agent wants to conform to their network in their behaviour in order to satisfy its social needs, which can be linked to injunctive norms and descriptive norms. Agents will communicate and ask the opinions, i.e., which behaviour they approve of (injunctive norms), and potentially view the behaviour of others in their network (descriptive norms).

In recent years, emphasis has increased on exploring group-level consequences, in which research illustrates the dynamics of a social environment as the result of individual behaviour (Latané, 1996). A core assumption is that an individual in a social environment is more likely to conform to the beliefs and opinions of the local majority than by both the local minority and by individuals in lower proximity. Models following this assumption predict clustering of opinions in social space, reduction in diversity, correlations across opinions by cluster members and continuing diversity. It must be noted here that agents in our model act on the basis of different needs, namely experiential, social and values needs (as will be further explained in Section 2.4). Consequently, the models deal with a higher-dimensional space, consisting of the satisfaction levels of these three needs.

Flache et al. (2017) illustrate the effects of different theoretical assumptions on group-level social dynamics in agent-based models containing social influence. Mainly focused on models of opinion dynamics (with continuous opinions), the authors distinguish between three main approaches (prominent model classes) and the core assumptions underlying these approaches:

1. Firstly there are *models of assimilative social influence*, which assume that connected individuals always have an influence on each other which reduces opinion differences (i.e., their opinions become more similar). These models will inevitably converge with a consensus of opinions.

2. Secondly, *models with similarity biased influence* include the assumption that individuals can influence towards reducing opinion difference depending on the similarity of their opinions or on additional psychological mechanisms, such as social identity and status (in other words, opinions become more similar depending on certain restrictions). In these models, a consensus is not given, but depending on similarity bias different homogeneous clusters can emerge.

3. Thirdly, there are *models with repulsive influence*, which assume that individuals being too dissimilar from one another can have a repulsive effect towards their opinions, such that social influence causes their difference in opinion to increase. The trigger and/or magnitude of the repulsive influence depends on the dissimilarity of their opinions

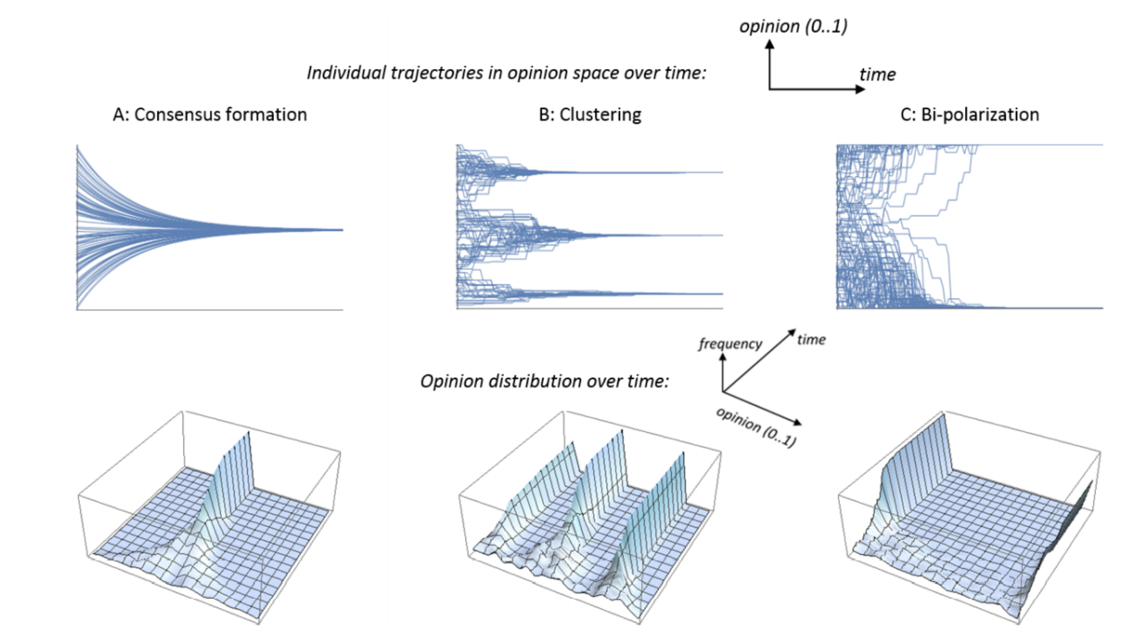



Figure 2.2: This Figure shows typical opinion dynamics generated by ABM's of social influence (Source: Flache et al. (2017, p. 5))

or on additional psychological mechanisms. These models again do not ensure consensus but can lead to bi-polarized clusters, where two maximally opposing views are adopted.

The typical effect on opinion dynamics of these prominent model classes is illustrated in Figure 2.2.

Also, hybrid forms exist, having ingredients from multiple categories of the prominent model classes. Flache et al. emphasize the need to relate to these categories and argue for identification of different critical assumptions and model choices, as well as comparison of and identifying relation to other models (Flache et al., 2017).

Where the previously discussed models of opinion dynamics include one variable of interest as the outcome, also models exist which investigate multiple variables. For instance, in addition to opinions on a given matter, one could investigate the individuals' fear or happiness with regards to that matter. As a result, the model has multiple dimensions of outcomes. The model is in this thesis is multi-dimensional, because it aims to investigate opinions on the COVID measures, willingness to follow the measures to prevent the virus from spreading and the need for social contact. For this purpose, a framework is needed that can model multi-dimensional simulation, as will be discussed in the following section.

## 2.4 HUMAT framework

The approach for the model in this thesis will be mainly based on the HUMAT integrated framework as described in Antosz et al. (2019). HUMAT was developed as a basic architecture in which one can construct artificial populations, containing agent cognitions, decision-making and social interactions based on social scientific theory. Related to HUMAT is the CONSUMAT framework Jager (2000), which integrates consumer needs with decision strategies. In contrast to HUMAT, CONSUMAT is mainly focused on individual consumer behaviour and therefore does not take into account phenomena such as cognitive dissonance and certain social processes and influences. Consequently, given the nature of the topic in this thesis, in which social interaction plays a big role, HUMAT seems like the better framework for developing the model.

In real-world social dynamics, individuals are connected in social networks. Individuals make decisions partly determined by their position in such a network, in which their own behaviour is based on the behaviour of and communication with different individuals. These interactions result in the diffusion of new behaviours, the formation of opinions groups, and the emergence of tipping points giving dominance to particular norms. Moreover, the individuals have their own interests, share information with others and are susceptible to norms. Taking these factors into account, HUMATs are repeatedly confronted with difficult choices, such as trade-offs between short-term gratification, social impacts and personal values (Antosz et al., 2019, p. 14).

Furthermore, in HUMAT the network is not a fixed entity, but rather reflects dynamic interactions between agents, where changes in interacting agents could lead to a change of the network. Agents may change with whom they interact and bond with new agents to interact with, based on opinions on a topic.

### 2.4.1 Needs

HUMAT agents' activity is determined by different behavioural alternatives, which are chosen based on the satisfaction of different *needs*. Three categories of needs are distinguished:

1. **Experiential needs**, relating to the immediate consequences of actions, such as costs and comfort.

2. **Social needs**, relating to the (non-)conformity within a social group: Belongingness, relatedness, social safety and social status within the network. For some agents, this need corresponds to conforming to peers' behaviour and behaving similarly, but for others 'being unique' could be a motivator not to conform.

3. **Values**, referring to values such as autonomy, biosphere and societal goals. These are typically related to more long term consequences of actions.

Linking these to our case study, the following needs can be modelled:

1. **Experiential needs:** Human beings have the need to experience coming into contact with friends in their network.

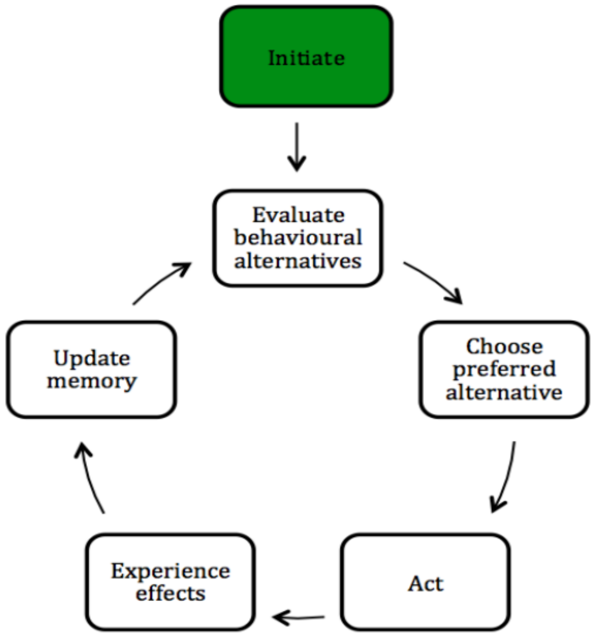



Figure 2.3: This Figure shows how HUMATs take action (Source: Antosz et al. (2019, p. 14))

2. **Social needs:** Human beings have the need to conform (or not conform in some cases) to others within their network, with regards to their opinion on the COVID measures. (Descriptive norms in Cialdini & Goldstein (2004)). Humans may respond to contact by attracting towards the opinions of the other, or by repulsion in some cases (Flache et al., 2017). Moreover, humans may also communicate/show their behaviour in terms of contact, which potentially differs from their opinion (*Injunctive norms* in Cialdini & Goldstein (2004)).

3. **Values:** Humans have personal values, entailing inclination to follow the measures in order to prevent the virus from spreading (*Personal Norms* in Cialdini & Goldstein (2004)).

### 2.4.2 Action

HUMATs act by choosing a behavioural alternative in order to maximize satisfaction levels of the individual categories of needs. HUMATs first evaluate the set of behavioural alternatives and assess the satisfaction levels of each alternative, then they choose the preferred one (the most satisfying alternative). After this, HUMATs experience the consequential effects, leading to an update of their memory. This process is depicted in Figure 2.3.

In many cases the behaviour only benefits a single or a subset of the categories, introducing the possibility of trade-offs between need categories. This may result in the experience of *cognitive dissonances* impacting the agents' information processing and chosen actions. Distinguishing between different categories allows for variance in satisfaction-depletion dynamics, which may be relatively quick for experiential needs (1), but slower for social needs

(2) and values (3). Decisions with regards to behaviour are made based on a weighted sum of the overall expected (dis)satisfaction from behavioural alternatives, determined by both expected satisfaction for a needs category, as well as the importance of that category for a particular HUMAT (Antosz et al., 2019, p. 15).

Cognitive dissonance is experienced when a behavioural alternative evokes sufficient levels for both satisfaction and dissatisfaction for one or more categories of needs, leading to a dilemma. Given the type of trade-off between categories of needs, one can identify three types of dilemmas, one for each category:

1. **Experiential dilemma**: Dissatisfaction on experiential needs and satisfaction of social needs and values or satisfaction on experiential needs and dissatisfaction of social needs and values.

2. **Social dilemma**: Dissatisfaction on social needs and satisfaction of experiential needs and values or satisfaction on social needs and dissatisfaction of experiential needs and values.

3. **Values dilemma**: Dissatisfaction on values and satisfaction of experiential and social needs or satisfaction on values and dissatisfaction of experiential and social needs.

Applied to our case, these dilemmas would correspond to the following examples, as an expected outcome of an action:

1. An **Experiential dilemma** could take place if a person is doubting having social contacts with friends in its network after seeing many friends. Continuing this behaviour would lead to experiential satisfaction, but would lead to dissatisfaction in their value need to prevent the virus from spreading. Also, their friends could show very different behaviour by not having as much social contact, leading to social dissatisfaction. Hence the expected dissatisfaction leads to a dilemma.

2. Someone could experience a **Social dilemma** when their behaviour and/or opinions are very different than that of their network. For example, on the one hand, a person is satisfied in their experiential and values needs, by balancing the number of social contacts it sees. Their network, on the other hand, is very polarized with some friends seeing many contacts, and others seeing none. Hence they experience social dissatisfaction, as their behaviour does not conform to that of their network.

3. A **Values dilemma** could be the opposite of the example given for the Experiential dilemma. On the one hand, the person could be satisfied with how well it is following the COVID measures but feel unsatisfied by the fact that it has not had enough contact with friends. Also, the friends show different behaviour by having lots of social contacts, leading to social dissatisfaction. Hence a dilemma exists between having social contact or not, because of this expected resulting dissatisfaction.

# 3 | MODEL

In Section 2.4, the theoretical outline of the HUMAT framework was described. This chapter discusses how the HUMAT framework was integrated in order to model the interaction between the COVID visitors measure and the need to experience physical contact. Firstly, in Section 3.1 a general overview is given in which the core elements of the model are discussed. Secondly, in Section 3.2 the algorithmic steps are described in-depth, followed by an overview of the main variables and parameters in Section 3.3.

## 3.1 Overview

The core of the model in this thesis is a set of HUMAT agents (referred to as *HUMATs*) that are connected in a network and act on the basis of different needs. On the one hand, HUMATs have the experiential need to come into physical contact with friends with whom they are connected. On the other hand, HUMATs have the values need to follow the *visitors measure*, which is a rule restricting them to only come into physical contact with a maximum number of friends each day in order to prevent COVID infections from spreading. Their need to follow the rule depends on their opinion about the rule, which is represented by

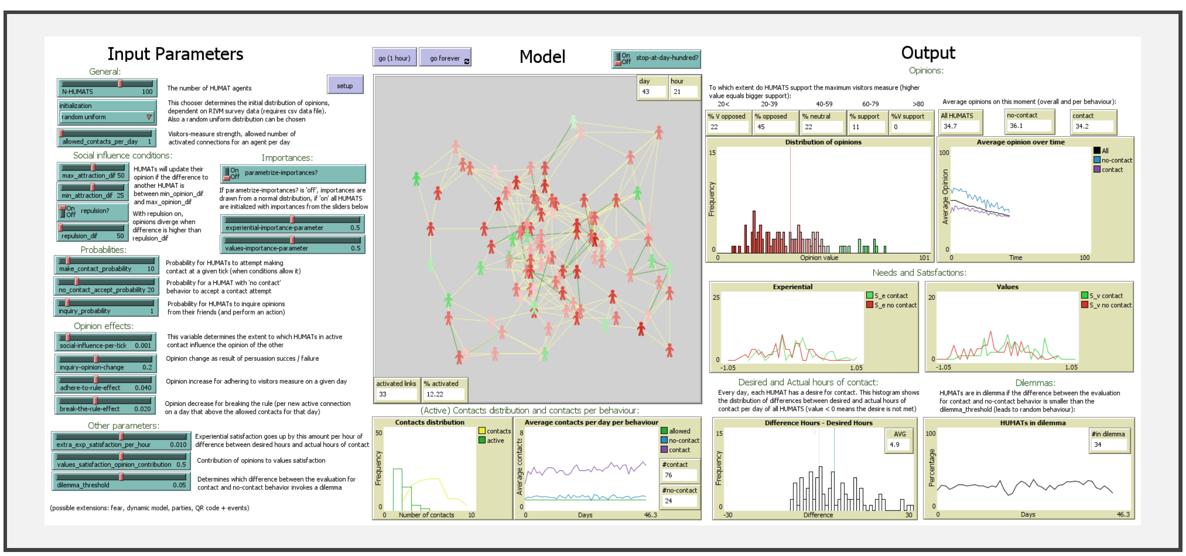



Figure 3.1: Screenshot of the full NetLogo model

an integer on a 0 to 100 scale. Here, a higher number represents stronger support for the rule. The opinions can be empirically initialized according to findings in data from surveys regarding support for the COVID measures from the RIVM (Dutch National Institute for Public Health and the Environment). This opinion is influenced by coming into physical contact with others. Furthermore, HUMATs feel the social need to conform to their networks with regard to their opinion.

Every 24 ticks in the simulation represent a new day for the HUMATs, with each tick representing one hour. It was chosen to model the simulation per hour since this provides the freedom to model the different actions and choices of the HUMATs on a given day, and many choices are dependent on inter-day rules and decision-making.

At the beginning of the day, HUMATs evaluate their experiential and values needs. According to this evaluation, the HUMATs decide whether their behaviour will be directed towards trying to follow the visitors measure, which is the *no-contact* behavioural alternative or to disregard the visitors measure, which is the *contact* behavioural alternative. If a HUMAT chooses the former, it will aim to adhere to the rule and try to not exceed the maximum allowed visitors that day. However, they might still exceed the rule if they are convinced by another HUMAT to make contact.

In each hour of the day, a HUMAT has a small chance to (online) inquire some of its connected friends about their opinions on the visitors measure. If the HUMAT is unsatisfied about how its own opinion relates to that of its friends, it can choose to adjust its own opinion or attempt to persuade one of its friends in changing their opinion. Moreover, HUMATs can request their friends to make physical contact with them, which has to be agreed upon by the receiving end. HUMATs with the *contact* behaviour will accept these requests, and HUMATs with the *no-contact* behaviour will only accept the request if they have not exceeded the allowed visitors from the visitors measure by having this physical contact. However, there is a probability that HUMATs with *no-contact* can be convinced to break this rule. Moreover, every hour HUMATs can choose to stop any active physical contact. HUMATs change their opinions such that it remains consistent with their behaviour: Breaking the rule by exceeding the maximum number of contacts on a day will cause HUMATs to dislike the visitors measure some more, which consequently leads to the HUMAT decreasing its support for the visitors measure and lowering its opinion. Furthermore, while HUMATs are in active contact, they socially influence each other concerning their opinions on the visitors measure.

At the end of each day, HUMATs will experience the effects of the social influence, as well as their behaviour on that day. In contrast to HUMATs breaking the rule, HUMATs that succeeded to follow the visitors measure increase their liking and consequently their support for the visitors measure, thereby increasing the value of their opinion (to remain consistent with their behaviour). These changes affect the needs of the HUMATs, which might cause them to choose different behaviour the next day.

Figure 3.1 shows the full NetLogo interface in which the simulation can be run. Appendix A displays additional screenshots of different parts of the model interface.

In the remainder of this section, the main components of the model are discussed in-depth. A flowchart giving a visual overview of the model can be found in Figure 3.2.

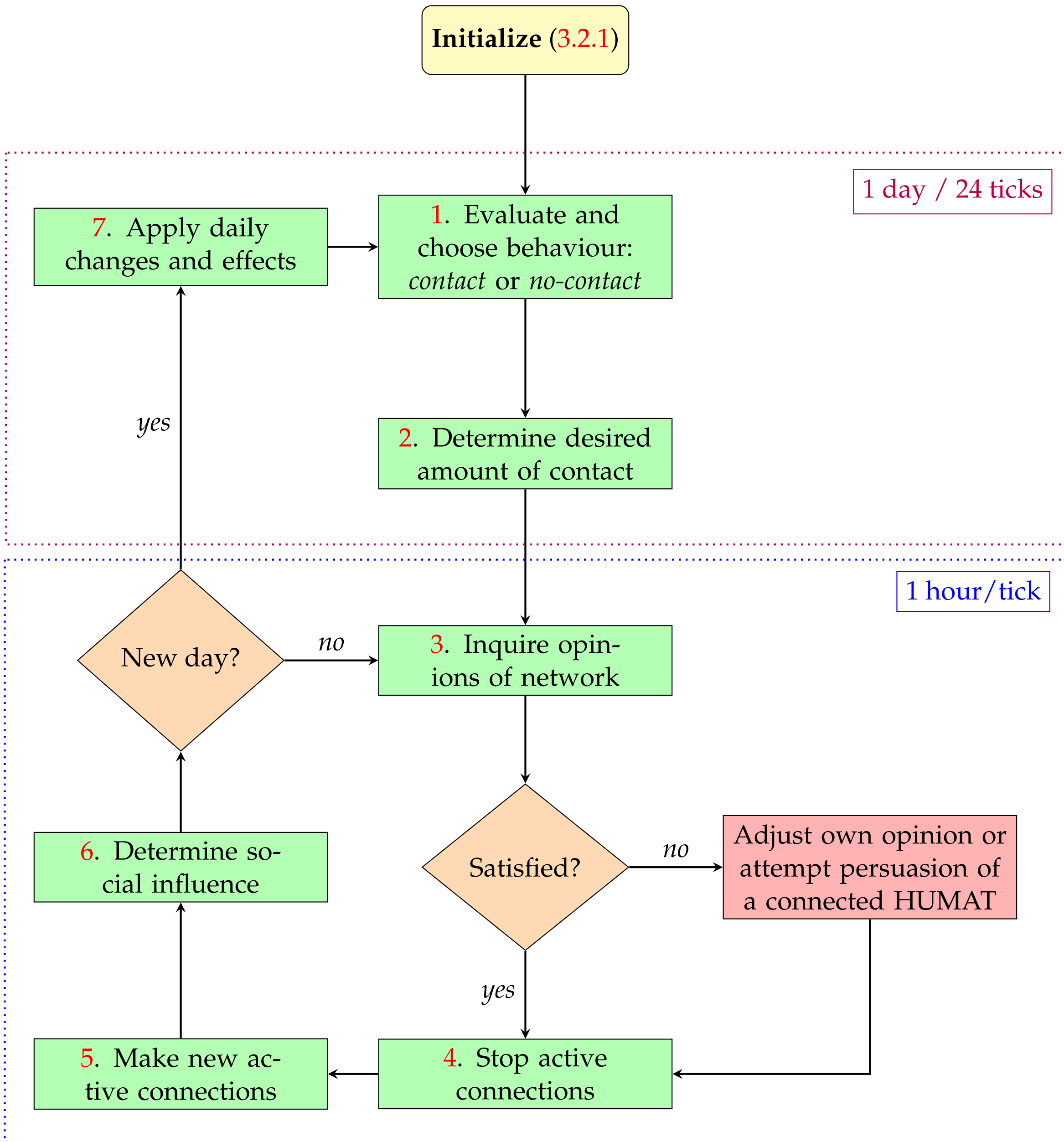



Figure 3.2: This Figure shows an overview of the model. It illustrates the main algorithmic steps and procedures that are executed within the model for every HUMAT. Note that some parts of the procedures rely on probabilities and will not be executed each iteration. All steps are further elaborated in Section 3.2.

## 3.2 Algorithmic steps

This section describes the algorithmic steps of the model more in-depth. Firstly, the initialization of the model is discussed. Afterwards, the different procedures that are executed while running the model are described.

### 3.2.1 Setup/Initialization of the model

The model is initialized (*Setup* in NetLogo), consisting of the following steps:

1. **Making and placing HUMATs:**
   $n$ HUMAT agents are initialized and placed randomly within an 80x80 square ($n = 100$ by default).

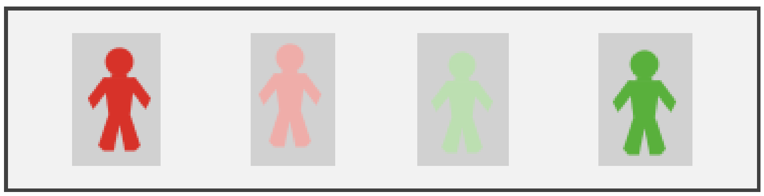


Figure 3.3: HUMAT agents. The different colors represent the HUMAT's opinion value (as discussed in step 3 of initialization). From left to right, low opinion (red) to high opinion (green).

2. **Create social networks (connections between HUMATs):**
   Each HUMAT creates a number of links to other HUMATs, which represent their friends. Firstly, a value is drawn from a normal distribution:

$$F_j = \lfloor \mathcal{N}(\mu, \sigma^2) \rceil \tag{3.1}$$

   where:

   - $F_j$ : is the number of connections HUMAT $j$ will make to others,
   - $\lfloor x \rceil$ : x is rounded to the nearest integer (with halves being rounded up, so $\lfloor 1.5 \rceil = 2$),
   - $\mu = 2$, and
   - $\sigma = 2$.

   This number is truncated between 1 and 10 and rounded to the nearest integer, with halves being rounded up (For upcoming mentions of rounding, note that we round halves up everywhere in the model). This number of connections will be made to other HUMATs. Thus, HUMATs instantiate at least one connection and a maximum of 10. Other HUMATs to connect with are searched for in proximity, for clear visualization of the network. The connections are bidirectional and both ends of a connection count as 'friends', so which of the HUMATs instantiates the connection is irrelevant. The average number of friends per HUMAT will end up higher than the mean of $\mu = 2$ in Equation 3.1. This is because $\mu = 2$ represents the mean number of connections that one HUMAT will form to other HUMATS, but consequently, also a friendship is formed for the other end. Moreover, the normal distribution is limited to be at least 1, while without this limit the average would be somewhat lower. Given these facts, on average HUMATs have approximately 5 friends in the simulation. Figure 3.4 shows connections between two HUMATs and a network of 100 HUMATs.

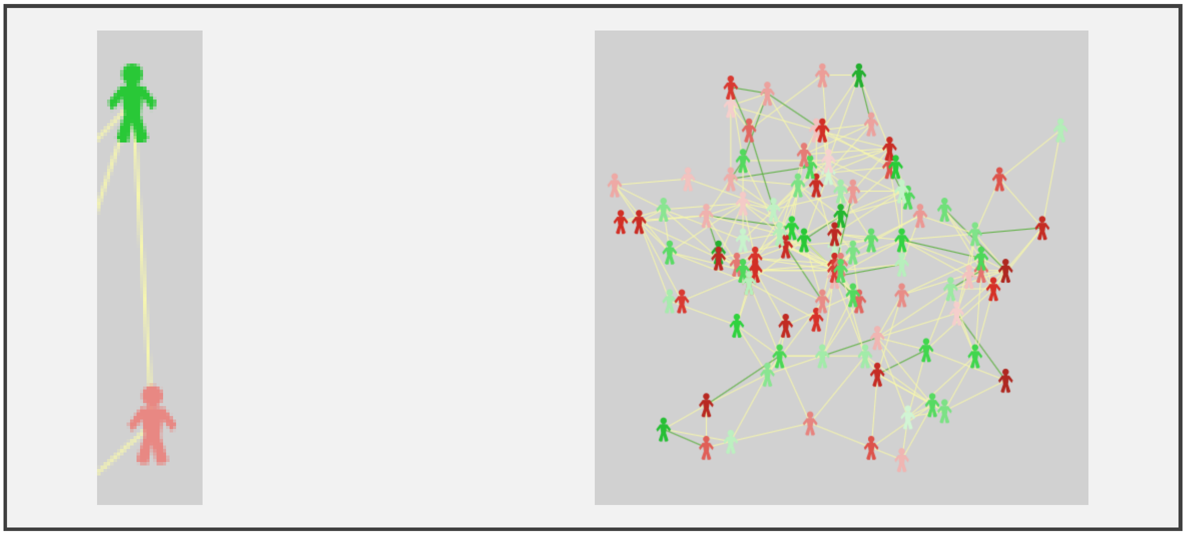


Figure 3.4: Two connected HUMATs (left) and a network of 100 HUMATs (right).

3. **Set opinions of HUMATs:**
   HUMATs are initialized with opinions, representing the support they have for the visitors measure. These are values between 0 and 100. The opinions can be initialized using different waves of an RIVM survey (of which the data can be seen in Table 3.1). In this survey, participants were asked to which extent they support the visitors measure. Their answers could be *Geen mening* (No opinion), *Helemaal niet* (Very opposed), *Niet* (Opposed), *Neutraal* (Neutral), *Wel* (Supportive) and *Helemaal Wel* (Very supportive). The table entries show the proportion of participants that gave these answers over several waves. In the model, the same distribution can be used, such that the entries are probabilities for the HUMATs to fall under the respective categories. Consequently, the distribution of opinions of the HUMATs in the model resembles the distribution of opinions in the survey.

| Survey Wave and Date | Vis/day | *Geen mening* | *Helemaal niet* | *Niet* | *Neutraal* | *Wel* | *Helemaal wel* |
|---|---|---|---|---|---|---|---|
| **6**: 19-23 aug 2020 | 6 | 0.9% | 4% | 7.3% | 11.8% | 27.9% | 48.1% |
| **7**: 30 sep - 4 oct 2020 | 4 | 0.5% | 3.1% | 7.4% | 11.9% | 30.6% | 46.5% |
| **8**: 11-15 nov 2020 | 2 | 0% | 5.8% | 10.5% | 13.7% | 28.9% | 41.1% |
| **9**: 30 dec 2020 - 3 jan 2021 | 2 | 0% | 3.3% | 6.6% | 10.9% | 30.7% | 48.5% |
| **10**: 10-14 feb 2021 | 1 | 0% | 9.2% | 18% | 17.1% | 27.2% | 28.5% |
| **11**: 24-28 mar 2021 | 1 | 0% | 10.4% | 23% | 19.3% | 25.3% | 22% |

Table 3.1: This Table shows RIVM survey results, in which participants are asked to state to which extent they support the measure of the maximum allowed contacts on a day (which we call *visitors measure*). Each row displays a different wave in which the survey is conducted, starting from august 2020 to march 2021. The column with *Vis/day* shows the allowed number of visitors according to the visitors measure. The percentages represent the proportion of participants that answered with the answer displayed on the top of the column. The data shows a decrease in support for the visitors measure as fewer visitors are allowed. More information regarding this survey can be found at https://www.rivm.nl/gedragsonderzoek/maatregelen-welbevinden/draagvlak.

Since the model requires quantities as opinions, the survey categories are converted to integers between 0 and 100, in which the higher the value of the opinion of a HUMAT is, the more it supports the visitors measure. Moreover, every HUMAT should have an opinion. Hence HUMATs that are initialized with the *No opinion* response get a random opinion, thereby distributing these respondents over the other categories[1]. The conversion from survey response to opinion value can be seen in Table 3.2:

| RIVM Survey Response | English Translation | Opinion in model |
|---|---|---|
| *Geen mening* | No opinion | 0-100 |
| *Helemaal niet* | Very opposed | 0-19 |
| *Niet* | Opposed | 20-39 |
| *Neutraal* | Neutral | 40-59 |
| *Wel* | Supportive | 60-79 |
| *Helemaal wel* | Very supportive | 80-100 |

Table 3.2: This Table shows the conversion from survey response to a continuous value for HUMATs in the model.

Alternatively, the opinion values of all HUMATs can be initialized randomly between 0 and 100. Furthermore, while running the model, HUMATs are coloured according to their opinion, as can be seen in Figure 3.3.

[1]We do not expect the responses with *no opinion* ('Geen mening' in the survey) to have a major influence, as the number of these responses is negligible

4. **Initialize importances of need-categories HUMATs:**
Each HUMAT is initialized with an importance for the experiential and value need-category. The value is drawn from a truncated normal distribution:

$$I_{k,j} = \mathcal{N}(\mu, \sigma^2) \tag{3.2}$$

where:

- $I_{k,j}$ : the importance of the $k$-th need category for HUMAT $j$,
- $\mu = 0.5$, and
- $\sigma = 0.14$.

and the value is truncated between 0 and 1. Alternatively, it is possible to manually parametrize the importances, such that all HUMATs are initialized with a certain value for their experiential and values need.

5. **Initialize satisfaction levels of HUMATs:**
In contrast to the HUMAT model described in Antosz et al. (2019), here we choose to model satisfaction levels similarly only with regards to the *experiential* and *value* need categories. The *social* needs will be addressed separately, which is discussed in step 3 of running the model. The satisfaction levels are applied to the two behavioural alternatives, which are *contact* ($c$) and *no-contact* ($n$) and will be used to determine which of these alternatives are chosen by the HUMATs. The satisfaction levels are values between -1 and 1, and are initialized as follows:

   - **Quantifying initial satisfactions:**
   The satisfaction levels for the different needs for the two behavioural alternatives require initial values, each with different considerations.

   For experiential needs, on the one hand, individuals differ in their expected satisfaction from experiencing physical contact, resulting in various expectations for following the behavioural attitude of *contact*. On the other hand, depending on factors such as an individual's feeling of safety with regards to having no contact, it will have a certain expectation from following the behavioural attitude of *no-contact*.

   For values needs, individuals differ in their satisfaction with respect to how they act (or don't act) in accordance with their norms and values. This results in different expectations for *contact* and *no-contact*.

   Here, we assumed that these feelings and considerations may differ per person and that the quantified values representing these feelings and expectations are normally distributed. Hence, for each HUMAT, a value is drawn from the following normal distribution for both *contact* and *no-contact* with respect to both the experiential and values needs:

$$S_{b,k,j} = \mathcal{N}(\mu, \sigma^2) \tag{3.3}$$

   where:

- $S_{b,k,j}$ : the expected satisfaction for the $k-$th group of needs for HUMAT $j$ with respect to behavioural alternative $b$ (*contact* or *no-contact*),
- $\mu = 0$, and
- $\sigma = 0.4$.

The outcome is truncated between -1 and 1. This value partly determines the experiential and values satisfaction a HUMAT expects from having the *no-contact* attitude. In addition, some characteristics of the HUMATs will be considered in evaluating behavioural alternatives, as will be discussed in step 1 of running the model.

### 3.2.2 Running the model

After the model is initialized, the model can be run (*Go (1 hour)* or *Go forever* in NetLogo). In each tick (or iteration), one hour progresses and the following procedures are executed:

1. **Evaluate and choose behavioural alternatives:** HUMATs first evaluate behavioural alternatives and then choose the preferred one:

   - **Evaluate behavioural alternative per need category:**
     HUMATs begin the day by evaluating the different behavioural alternatives with respect to the expected satisfaction of their different needs. For the *experiential* (e) and *value* (v) need categories and evaluation is made, in which some characteristics of the HUMATs are taken into account.

     - **Characteristics that influence experiential evaluation:** For the evaluation of the experiential evaluation, additional parameter $\eta_j$ is added to the initial expected experiential satisfaction (determined in Equation 3.3), which considers differences in desired hours of contact and actual hours of contact for HUMAT $j$ :

$$E_{b,e,j} = (S_{b,e,j} \pm \eta_j) * I_{e,j} \tag{3.4}$$

       where:
       * $E_{b,e,j}$ : the evaluation for the experiential needs for HUMAT $j$ with respect to behavioural alternative $b$,
       * $S_{b,e,j}$ : the expected satisfaction for the experiential needs for HUMAT $j$ with respect to behavioural alternative $b$,
       * $I_{e,j}$ : the importance of the experiential needs for HUMAT $j$,
       * $\eta_j$ : additional expected experiential satisfaction based on differences in desired hours of contact and actual hours of contact for HUMAT $j$. For *contact*, $\eta_j$ is added to the initial satisfaction, while for *no-contact* it is subtracted. Initially $\eta_j$ is set to 0.

Since the value for $\eta_j$ is determined at the end of each day, it is discussed in step 7.

– **Characteristics that influence values evaluation:** For the evaluation of the values evaluation, additional parameter $\xi_j$ is added to the initial expected value satisfaction (determined in Equation 3.3), which considers the opinion of HUMAT $j$:

$$E_{b,v,j} = (S_{b,v,j} \pm \xi_j) * I_{v,j} \tag{3.5}$$

where:

* $E_{b,v,j}$ : the evaluation for the values needs for HUMAT $j$ with respect to behavioural alternative $b$,
* $S_{b,v,j}$ : the expected satisfaction for the values needs for HUMAT $j$ with respect to behavioural alternative $b$,
* $I_{v,j}$ : the importance of the values needs for HUMAT $j$,
* $\xi_j$ : additional expected values satisfaction based on the opinion of HUMAT $j$. Value determined by Equation 3.6.

Depending on the opinion a HUMAT has, $\xi_j$ is determined is determined by converting the value of the opinion (which is between 0 and 100) to a -1 to 1 scale and multiplying it by a weight ($\psi$):

$$\xi_j = \psi * \frac{O_j * 2 - 100}{100} \tag{3.6}$$

where:

* $O_j$ : the opinion of HUMAT $j$, and
* $\psi_j$ : a weight that determines the contribution of a HUMATs $j$'s opinion to its value evaluation. It is set to 0.5.

Since a high opinion means larger support for following the rule, $\xi_j$ is subtracted from (3.7) and added to (3.8) HUMAT $j$'s expected values satisfaction for *contact* and *no-contact* respectively. Hence, Equation 3.4 will be executed for *contact* by

$$E_{contact,v,j} = (S_{contact,v,j} - \xi_j) * I_{v,j}, \tag{3.7}$$

and for *no-contact* by

$$E_{no-contact,v,j} = (S_{no-contact,v,j} + \xi_j) * I_{v,j}. \tag{3.8}$$

- **Determine expected satisfaction per behavioural alternative:**
For each need category, the expected satisfaction is multiplied by the importance of that category. The sum of these results will be the overall expected satisfaction for a behavioural alternative:

$$S_{b,j} = \frac{(S_{b,e,j} \pm \eta_j) * I_{e,j} + (S_{b,v,j} \pm \xi_j) * I_{v,j}}{2} = \frac{E_{b,e,j} + E_{b,v,j}}{2} \tag{3.9}$$

where:

  - $S_{b,j}$ : the overall expected satisfaction for behavioural alternative $b$ for HUMAT $j$,
  - $S_{b,k,j}$ : the expected satisfaction for the $k-$th group of needs for HUMAT $j$ with respect to behavioural alternative $b$,
  - $I_{k,j}$ : the importance of the $k$-th need category for HUMAT $j$, and
  - $E_{b,k,j}$ : evaluation of behavioural alternative $b$ with respect to the $k$-th need category for HUMAT $j$.

- **Choose preferred behavioural alternative:** Based on the values for $S_{contact,j}$ and $S_{no-contact,j}$ HUMATs will choose their preferred behavioural alternative. In principle, this is the behaviour with the highest expected satisfaction. However, if $S_{contact,j}$ and $S_{no-contact,j}$ are very similar, HUMATs will experience a *dilemma* and have difficulty choosing one of the behaviours. Specifically, if $\mid S_{contact,j}$ - $S_{no-contact,j} \mid$ is lower than or equal to some threshold value $\kappa$, the satisfactions for the behavioural alternatives are so close that HUMAT $j$ will experience a dilemma. As a consequence, it will choose a behaviour randomly. The behaviour is determined by Equation 3.10:

$$B_j = \begin{cases} contact & \text{if } S_{contact,j} > S_{no-contact,j}, \\ no-contact & \text{if } S_{contact,j} < S_{no-contact,j}, \text{ and} \\ dilemma \rightarrow \text{random choice} & \text{if } \mid S_{contact,j} \text{ - } S_{no-contact,j} \mid \leq \kappa. \end{cases} \tag{3.10}$$

where:

  - $B_j$ : Behaviour choice of HUMAT $j$ (*contact* or *no-contact*),
  - $S_{b,j}$ : the overall expected satisfaction for behavioural alternative $b$ for HUMAT $j$, and
  - $\kappa$ : dilemma threshold. Set to 0.05.

As changes will be applied after 24 hours, the HUMATs will also only perform the step of choosing a behaviour at the beginning of each day.

2. **Determine desired amount of contact:**
With respect to the number of connections a HUMAT has, it will have the internal desire for a certain amount of contact every day. In order to quantify this desire, at the beginning of each day all HUMATs set a number of desired hours of contact for the day. Note that these hours are aggregated per active contact, meaning that two hours of contact are equal to one tick of being in an active connection with two different friends. For HUMATs with more friends, we assume they are more extroverted and gain a more positive effect from engaging in social interaction (Augustine & Hemenover, 2012). Therefore HUMATs with a higher number of connections will desire more contact than HUMATs with a lower number of connections. Hence, the determined amount of desired contact takes into account the number of connections a HUMAT has by means of a sigmoid function. However, to vary this desire day by day, some stochastics are included by means of a normal distribution. Equation 3.11 shows how the number of hours is determined:

$$D_j = \mathcal{N}(\mu, \sigma^2) + \frac{2 * \alpha}{1 + e^{-(x_j - \bar{x})}} - \alpha, \tag{3.11}$$

where:

- $D_j$ : the desired number of hours of contact for HUMAT $j$,
- $\mu = 10$,
- $\sigma = 4$,
- $x_j$ : the number of contacts of HUMAT $j$,
- $\bar{x}$ : the average number of contacts of all HUMATs, and
- $\alpha$ : the range of the sigmoid function. It is set to 5, meaning this function will add a number between -5 and 5, depending on the relative number of contacts HUMAT $j$ has.

The outcome of Equation 3.11 is truncated between 0 and 40 and rounded to the nearest integer. At the end of the day, this value will be compared to their actual hours of contact, which will influence their experiential needs with regards to contact, as will be discussed in step 7.

3. **Inquire opinions of network:**
Regardless of their behavioural alternative, HUMATs have a 1% probability to inquire about the opinions of a selection of their network. This probability is chosen as it will result in HUMATs inquiring roughly every four days. We assume this is a process that happens online and therefore has different effects from physical contact in step 6. In this step, the aim is to capture the **social need** of conforming to the network, by letting HUMATs investigate how their opinion relates to that of a selection of their friends. If a HUMATs opinion is sufficiently different from the opinion of those friends, an action to resolve the difference is triggered. Firstly, two measurements are discussed, along with how they relate to the probability to act. Afterwards, the actions a HUMAT can take to resolve differences are described. After a selection is made by taking a random subset of HUMAT $j$'s network, the following two measurements are made:

- The difference between HUMAT $j$'s opinion and the average opinion of the selection of HUMAT $j$'s network:

$$\textbf{Difference from average}_j = \bar{O}(j) - O_j \tag{3.12}$$

where:

  - $O_j$ : HUMAT $j$'s opinion, and
  - $\bar{O}(j)$ : the average opinion of the selection of HUMAT $j$'s.

- The mean difference between HUMAT $j$'s opinion and the individual opinions of the selection of HUMAT $j$'s network:

$$\textbf{Mean difference from selected friends}_j = \frac{1}{n}\sum_{m=1}^{n} |O_m - O_j| \tag{3.13}$$

where:

  - $O_j$ : HUMAT $j$'s opinion,
  - $O_m$ : Opinion of HUMAT $m$ from the selection of HUMAT $j$'s friends, and
  - $n$ : the number of friends in the selection of HUMAT $j$'s network.

The value for the mean difference from the selected friends from Equation 3.13 determines whether HUMAT $j$ will perform an action to resolve differences. If this value is 30 or higher, HUMAT $j$ experiences cognitive dissonance from a social dilemma and will perform such an action. Below 30, the value is equal to the probability HUMAT $j$ will perform an action. With this method, we assume that HUMATs that differ more from their network with regards to their opinion of the visitors measure, feel a higher social need to resolve this difference, and hence are more likely to act in order to resolve it.

If one of the aforementioned requirements is met and HUMAT $j$ decides to perform an action, it can do one of two things, with an equal probability of 50%:

- **Adjust own opinion:**
  HUMAT $j$ adjusts its own opinion towards the mean of the selected friends. It applies a proportion ($\omega$) of the difference to the average (from Equation 3.12) to its own opinion[2]:

$$\Delta O_j = \Delta O_j + \omega * \textbf{Difference from average}_j \tag{3.14}$$

  where:

  - $\Delta O_j$ : The difference in opinion this day for HUMAT $j$, and

[2] Note that opinion-changing effects are not applied immediately, but stored as a 'difference' to be applied after each day.

* $\omega$ : the weight of the opinion change, set to 0.2.

- **Attempt to persuade another HUMAT:**
HUMAT $j$ attempts to persuade another HUMAT from its selected friends to change its opinion towards that of HUMAT $j$. Persuading can have two outcomes: it either *succeeds* or *fails*, both with an equal probability of 50%[3]. A persuasion success for HUMAT $j$ will result in changing the opinion of the other HUMAT towards it. We also assume that a persuasion fail will have the opposite effect, i.e., that the other HUMAT will be more radical in its opinion with regards to HUMAT $j$, by increasing the difference. The effects of persuasion success and failure are as follows:

**Persuasion success:** HUMAT $j$ persuades HUMAT $i$, consequently HUMAT $i$ changes its opinion towards HUMAT $j$:

$$\Delta O_i = \Delta O_i + \omega * (O_j - O_i) \tag{3.15}$$

where:
* $O_j$ : HUMAT $j$'s opinion,
* $O_i$ : HUMAT $i$'s opinion,
* $\Delta O_i$ : The difference in opinion this day for HUMAT $i$, and
* $\omega$ : the weight of the opinion change, set to 0.2.

**Persuasion failure:** HUMAT $j$ fails to persuade HUMAT $i$, consequently HUMAT $i$ changes its opinion away from that of HUMAT $j$:

$$\Delta O_i = \Delta O_i - \omega * (O_j - O_i) \tag{3.16}$$

where:
* $O_j$ : HUMAT $j$'s opinion,
* $O_i$ : HUMAT $i$'s opinion,
* $\Delta O_i$ : The difference in opinion this day for HUMAT $i$, and
* $\omega$ : the weight of the opinion change, set to 0.2.

4. **Stop active connections:**
Each HUMAT can stop any active connection (which are made in the step 5) with a 15% probability. Note that one connection can therefore be stopped by HUMATs on either side. The 15% probability is chosen here, as it will result in connections remaining active for approximately 3 to 4 hours on average.

[3] 'Stubbornness' could be a potential extension to make this more realistic.

5. **Make new active connections:**
In contrast to step 3, which captures online contact, here active connections between HUMATs are assumed to entail physical contact[4]. HUMATs can attempt to make connections, but the other end has to accept the request in order to activate a connection:

    - **Requesting an active connection:** In this step HUMATs attempt to activate a connection with one of the friends in their network. HUMATs with the *no-contact* behavioural alternative who have not yet reached the allowed number of contacts this day and HUMATs who have the *contact* behavioural alternative (regardless of the number of contacts it had this day) have a 10% probability to make a request for making an active connection with another HUMAT in their network per tick.
    - **Accepting a request for an active connection:** The HUMAT who receives a request for an active connection has to accept the request. HUMATs with *no-contact* behavioural alternative who have not yet reached the allowed number of contacts per day and HUMATs who have the *contact* behavioural alternative (regardless of the number of contacts it had this day) will always accept the contact. For HUMATs with the behaviour *no-contact* who have reached the maximum contacts per day allowed by the visitors measure, there is a probability of 80% that they deny a request for contact. Hence, that leaves a 20% probability that such a HUMAT can be convinced by the requesting HUMAT to still accept an active contact, despite the fact that it will exceed the maximum allowed number of contacts. This probability, therefore, represents the chance a HUMAT who aims to follow the visitors measure goes against its own principles.

      If in any case the contact is accepted, the connection (called a *link* in NetLogo) between the two HUMATs activates and turns green (see Figure 3.5).

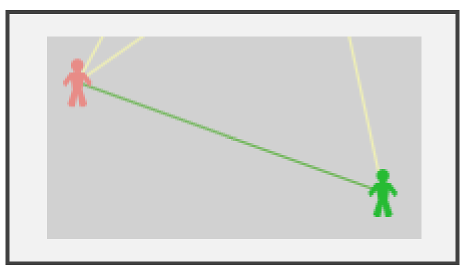


Figure 3.5: Two HUMATs that are in an active connection.

After instantiating or accepting an active connection, HUMATs that **break the rule of the visitors measure** by going over the limit of allowed contacts per day, slightly reduce the value of their opinion:

[4]Note that for this thesis, we assume that the agents represent a group of young adults who live on their own. In real life, many young adults might also live with roommates with whom they spontaneously meet and come into contact, which potentially could satisfy their experiential need for social contact. In order to keep the model simple, we assume no such spontaneous forms of social contact will happen, but that social contact between HUMATs is always the result of two HUMATs that live apart and decide to physically meet. In other words, this model specifically focuses on the need for *external* social contact.

$$\Delta O_j = \Delta O_j - \rho * O_j \tag{3.17}$$

where:

- $\Delta O_j$ : The difference in opinion this day for HUMAT $j$,
- $O_j$ : HUMAT $j$'s opinion, and
- $\rho$ : the weight for breaking the rule, a random float with $0 <= \rho <= 0.02$

By reducing the opinion percentage-wise, HUMATs with the *no-contact* behavioural alternative that decide to break the rule they claim to support are relatively more affected. This is because these HUMATs in general have a higher valued opinion in accordance with their support for the visitors measure than HUMATs who already support the rule to a lesser extent. From the perspective of consistency, it seemed that a percentage-wise reduction is in its place here.

6. **Determine social influence on active connections:**
At each tick/iteration, the opinions of the HUMATs are influenced by the HUMATs with whom they have an active connection. For this step, in addition to the first-order connections, also higher-order connections are taken into account. Together, they form a *cluster of active connections*. Figure 3.6 shows such a cluster and clarifies what is meant[5].

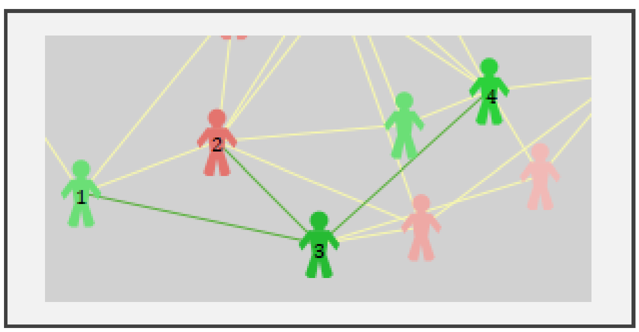



Figure 3.6: Cluster of active connections. In this Figure, HUMAT 3 has a first-order connection to HUMATs 1, 2 and 4. HUMATs 1 and 2 could have a first-order connection to each other, but in this case are connected through a higher-order connection via HUMAT 3. Both HUMAT 1 and 2 are connected to HUMAT 4 through a higher-order connection via HUMAT 3.

Each HUMAT in a cluster of active connections is assumed to be socially influenced by each other HUMAT, meaning that their opinion is adjusted according to the other HUMATs. The influence depends on parameters regarding the difference in opinion between two HUMATs. It is modelled such that when this difference is lower than

[5]In the example of Figure 3.6, in principle HUMAT 1 and 2 could also have a connection. This would result in exactly the same cluster, and therefore has no additional effect with regards to social influence.

10, HUMATs will accept this difference, causing the opinions not to be affected by each other, following from the assumption that human beings with minor differences in opinion will tolerate one another. In other cases, *attraction* and *repulsion* will take place (see Sherif & Hovland (1961) for a discussion on the role of assimilation and contrast effects and their influence on processes of communication, persuasion and social judgment):

- **Attraction:** For opinion differences higher than 25, but lower than or equal to 50, HUMATs in a cluster of active connections will have an attracting influence: From the perspective of HUMAT $j$, if HUMAT $j$ is in active contact with HUMAT $i$ and $25 < |O_j - O_i| <= 50$, HUMAT $j$ changes its opinion towards HUMAT $i$, as a proportion ($\gamma$) of the difference:

$$\Delta O_j = \Delta O_j + \gamma * (O_i - O_j) \tag{3.18}$$

  where:
  - $\Delta O_j$ : The difference in opinion this day for HUMAT $j$,
  - $O_j$ : HUMAT $j$'s opinion,
  - $O_i$ : HUMAT $i$'s opinion, and
  - $\gamma$ : the weight for social influence per tick/iteration, set to 0.001.

- **Repulsion:** As an optional parameter, HUMATs can also have a repulsive effect on each other's opinions. For opinion differences higher than 50, HUMATs in a cluster of active connections will have a repulsing influence, which has the opposite effect from Equation 3.18: From the perspective of HUMAT $j$, if HUMAT $j$ is in active contact with HUMAT $i$ and $|O_j - O_i| > 50$, HUMAT $j$ diverges from HUMAT $i$ by changing its opinion away from that of HUMAT $i$:

$$\Delta O_j = \Delta O_j - \gamma * (O_i - O_j) \tag{3.19}$$

  where:
  - $\Delta O_j$ : The difference in opinion this day for HUMAT $j$,
  - $O_j$ : HUMAT $j$'s opinion,
  - $O_i$ : HUMAT $i$'s opinion, and
  - $\gamma$ : the weight for social influence per tick/iteration, set to 0.001.

After this point, for each HUMAT the number of active contacts is counted and added to the total of that day. In contrast to opinion influence where a cluster of active connections was considered, for determining the hours of contact we only consider first-order connections. The hours are stored in order to compare it at the end of the day in step 7 to the desired hours of contacts from step 2. Note again that hours are aggregated over different active contacts, meaning that two hours of contact are equal to one tick of having an active connection with two different friends. The hours of contact per tick $t$ for HUMAT $j$ are determined by Equation 3.20:

$$H_j = H_j + H_j^t \tag{3.20}$$

where:

- $H_j$ : the total hours of contact this day for HUMAT $j$, and
- $H_j^t$ : the number of active contacts for HUMAT $j$ at tick $t$.

7. **Apply daily changes and effects:**
In this step, which is executed at the end of each day (24 ticks/iterations), the effects with regard to opinion changes and desired contacts for the day are determined.

    - **Opinion changes:**
    Firstly, HUMATs that have **adhered to the visitors measure** on a day have their opinion slightly increased. This follows from the assumption that if a rule is compatible with the behaviour someone shows, one should be somewhat more supportive of that rule. The difference is as follows:

    $$\Delta O_j = \Delta O_j + \tau * (100 - O_j) \tag{3.21}$$

    where:
        - $\Delta O_j$ : The difference in opinion this day for HUMAT $j$,
        - $O_j$ : HUMAT $j$'s opinion, and
        - $\tau$ : the weight for adhering to the rule, a random float with $0 <= \tau <= 0.04$

    In accordance with the opposite effect in Equation 3.17, the added opinion difference is percentage-wise on the inverse of a HUMATs opinion. Applying Equation 3.21 like this entails that HUMATs with the *contact* behavioural alternative (who in general have a lower opinion) that decide to follow the rule they claim to oppose, have their opinion increased more than HUMATs who already support to rule to a higher extent.
    Afterwards, the opinion changes from Equations 3.14, 3.15, 3.16, 3.17, 3.18, 3.19 and 3.21 are applied to the HUMATs opinions. Changing opinions after a day instead of immediately circumvents potential problems with applying opinion changes to HUMATs in a certain order. For every HUMAT $j$ the total stored difference in opinion that day is multiplied with a stubbornness weight $\zeta_j$, which is a random float between 0 and 1 that determines the extent to which HUMAT $j$ allows changes to its opinion. The result of this multiplication is added to the opinion of HUMAT $j$:

    $$O_j = \lfloor O_j + \zeta_j * \Delta O_j \rceil \tag{3.22}$$

where:

- $\Delta O_j$ : The difference in opinion this day for HUMAT $j$,
- $O_j$ : HUMAT $j$'s opinion,
- $\zeta_j$ : Stubbornness weight for HUMAT $j$, and
- $\lfloor x \rceil$ : x is rounded to the nearest integer (with halves being rounded up, so $\lfloor 1.5 \rceil = 2$)

As a consequence of the opinion change, the HUMATs' expected satisfaction levels for values needs are adjusted accordingly (by Equations 3.6, 3.7 and 3.8).

- **Difference between desired and actual hours of contact:**
The desired hours of contact $D_j$ from Equation 3.11 are compared to the actual hours of contact $H_j$. The difference between $H_j$ and $D_j$ will determine the additional satisfaction parameter $\eta$ from Equation 3.4. This means it will be added (3.23) and subtracted (3.24) to HUMAT $j$'s expected experiential satisfaction for *contact* and *no-contact* respectively. Hence Equation 3.4 will be executed for *contact* by

$$E_{contact,e,j} = (S_{contact,e,j} + \eta_j) * I_{e,j}, \tag{3.23}$$

where:

- $E_{contact,e,j}$ : the evaluation for *contact* with respect to the experiential needs for HUMAT $j$,
- $S_{contact,e,j}$ : the expected satisfaction for *contact* with respect to the experiential needs for HUMAT $j$,
- $I_{e,j}$ : the importance of the experiential needs for HUMAT $j$, and
- $\eta_j$ : additional satisfaction parameter for experiential satisfaction for HUMAT $j$.

and for *no-contact* by

$$E_{no-contact,e,j} = (S_{no-contact,e,j} - \eta_j) * I_{e,j}. \tag{3.24}$$

where:

- $E_{no-contact,e,j}$ : the evaluation for *no-contact* with respect to the experiential needs for HUMAT $j$,
- $S_{no-contact,e,j}$ : the expected satisfaction for *no-contact* with respect to the experiential needs for HUMAT $j$,
- $I_{e,j}$ : the importance of the experiential needs for HUMAT $j$, and
- $\eta_j$ : additional satisfaction parameter for experiential satisfaction for HUMAT $j$.

In these function, $\eta_j$ is determined as follows:

$$\eta_j = \begin{cases} \eta_j - \chi * (H_j - D_j) & \text{if } H_j > D_j, \\ \eta_j + \chi * (D_j - H_j) & \text{if } H_j < D_j, \\ \eta_j & \textit{otherwise} \end{cases} \tag{3.25}$$

where:

- $H_j$ : the total hours of contact this day for HUMAT $j$,
- $D_j$ : the desired number of hours of contact this day for HUMAT $j$,
- $\eta_j$ : additional satisfaction parameter for experiential satisfaction of HUMAT $j$, which is limited to a value between 0 and 1, and
- $\chi$ : weight for adjustments to $\eta_j$ per hour of difference between desired hours $D_j$ of contact and actual hours of contact $H_j$ (set to 0.01).

In practice, $\eta_j$ will vary between 0 and 1 and increases while a HUMAT $j$ has less contact than it desires ($H_j < D_j$) and decrease while HUMAT $j$ has less contact than it desires ($H_j > D_j$). If $\eta_j$ increases, HUMAT $j$ will expect more satisfaction for *contact* and fewer satisfaction for *no-contact*. Hence, as a consequence of not having as much contact as HUMAT $j$ desires, it it more likely to choose *contact* as its behaviour.

## 3.3 Model Variables

This section gives an overview of the main variables in the model. Tables show names of variables, their descriptions, types and value ranges. Table 3.3 displays the general adjustable model parameters and Table 3.3.2 displays HUMAT specific variables.

### 3.3.1 Adjustable Parameters

| Parameter name | Description | Type | Range |
|---|---|---|---|
| • N-HUMATs | The number of agents | INT | [10, 150] |
| • initialization | Determines initial distribution of opinions according to one of the RIVM survey waves from Table 3.1 or a random uniform distribution. | CHOOSER | 7 Options |
| • allowed_contacts_per_day | Strength of the visitors measure, allowed number of activated connections for a HUMAT per day. | INT | [1,10] |
| • max_attraction_dif (= max in next rows) | Maximal difference in opinion between HUMATs in order for *attraction of opinions* to take place | INT | [1,100] |
| • min_attraction_dif | Minimal difference in opinion between HUMATs in order for *attraction of opinions* to take place | INT | [0, max ] |
| • repulsion? | Option to include repulsion effects | BOOLEAN | [0,1] |
| • repulsion_dif | Minimal difference in opinion between HUMATs in order for *repulsion of opinions* to take place | INT | [max , 100 ] |
| • make_contact_probability | Probability for HUMATs to make contact at a given tick, when conditions are met (default = 10%) | INT | [0,100] |
| • no_contact_accept_ probability | Probability for HUMATs with *no-contact* behaviour to accept contact attempt (default = 20%) | INT | [0,100] |
| • inquiry_probability | Probability for HUMATs to inquire opinions from network (default 1%) | INT | [0,100] |
| • social-influence-per-tick | Value for $\gamma$ (default = 0.001) | FLOAT | [0,0.01] |
| • inquiry-opinion-change | Value for $\omega$ (default = 0.2) | FLOAT | [0,0.5] |
| • adhere-to-rule-effect | Value for $\tau$ (default = 0.04) | FLOAT | [0,0.04] |
| • break-the-rule-effect | Value for $\rho$ (default = 0.02) | FLOAT | [0,0.02] |
| • extra_exp_satisfaction_ per_hour | Additional expected satisfaction for *contact* based on desires and actual contact. Value for $\eta$ (default = 0.01) | FLOAT | [0,0.2] |
| • values_satisfaction_opinion_ contribution | Determines the extent to which the HUMATs' opinions contribute to the values needs. Value for $\xi$ (default = 0.5) | FLOAT | [0,1] |
| • dilemma_threshold | Value for $\kappa$. Determines when $\mid S_{contact,j}$ - $S_{no-contact,j} \mid$ invokes a dilemma. | FLOAT | [0,0.1] |
| • parametrize-importances? | Determines whether importances are drawn from a normal distribution or parametrized manually | BOOLEAN | [0,1] |
| • experiential-importance- parameter | Manually set experiential importance for all HUMATs (if parametrize-importances? is on) | FLOAT | [0.1] |
| • values-importance- parameter | Manually set values importance for all HUMATs (if parametrize-importances? is on) | FLOAT | [0.1] |

Table 3.3: General adjustable model parameters.

### 3.3.2 HUMAT Agents (nodes):

| Variable name | Description | Type | Range |
|---|---|---|---|
| • n_friends | The number of friends a HUMAT has, active or not | INT | >= 1 |
| • n_active_connections | The number of active connections a HUMAT has currently | INT | >= 0 |
| • n_contacts_this_day | The number of active connections a HUMAT has had on a day | INT | >= 0 |
| • hours_of_contact_this_day | The aggregated number of hours a HUMAT had active connections with other HUMATs on a day ($H_j$) | INT | >= 0 |
| • desired_hours_of_contact_this_day | The desired number of hours a HUMAT has on a day ($D_j$) | INT | >= 0 |
| • opinion_measure | The opinion on the COVID maximum visitors measure ($O_j$) | INT | $[0,100]$ |
| • opinion_difference_this_day | This variable stores the adjustments to a HUMAT's opinion that are made on a given day. The difference is applied to the HUMAT's opinion after each day ($\Delta O_j$) | FLOAT | - |
| • behaviour | Behavioural alternative. *contact* or *no-contact* ($B_j$) | STRING | 2 options |
| • stubbornness | Determines the extent to which a HUMAT allows changes to its opinion (value for $\zeta$) | FLOAT | [0,1] |
| • experiential-importance | The importance for the experiential category ($I_{e,k}$) This is a weighting factor, determining how important a HUMAT finds experiential satisfaction. | FLOAT | [0,1] |
| • values-importance | The importance for the values category ($I_{v,k}$) This is a weighting factor, determining how important a HUMAT finds values satisfaction. | FLOAT | [0,1] |
| • experiential-satisfaction-contact | Expected satisfaction of HUMAT $j$'s experiential needs for *contact* behaviour ($S_{contact,e,j}$) | FLOAT | [-1,1] |
| • values-satisfaction-contact | Expected satisfaction of HUMAT $j$'s value needs for *contact* behaviour ($S_{contact,v,j}$) | FLOAT | [-1,1] |
| • experiential-satisfaction-no-contact | Expected satisfaction of HUMAT $j$'s experiential needs for *no-contact* behaviour ($S_{no-contact,e,j}$) | FLOAT | [-1,1] |
| • values-satisfaction-no-contact | Expected satisfaction of a of HUMAT $j$'s values needs for *no-contact* behaviour ($S_{no-contact,v,j}$) | FLOAT | [-1,1] |
| • Satisfaction-contact | Expected satisfaction for *contact* behaviour ($S_{contact,j}$) | FLOAT | [-1,1] |
| • Satisfaction-no-contact | Expected satisfaction for *no-contact* behaviour ($S_{no-contact,j}$) | FLOAT | [-1,1] |

Table 3.4: HUMAT specific variables.

# 4 | Experiments & Results

Chapter 3 described the implementation of the model. Now the model can be run to explore different scenarios and observe how a simulated network of HUMATs responds to these scenarios. More specifically, we can observe the effects of changes in the strictness of the visitors measure and populations of HUMATS with different importances on phenomena such as the distribution of opinions, the total number of active contacts, the number of dilemmas the HUMATs experience and the decision making of individual HUMATs throughout time as a result.

This chapter describes various experiments that have been performed with the model and the results that follow from these experiments: Firstly, Section 4.1 describes a set of experiments with RIVM data initializations, in which RIVM survey data is used to initialize the HUMATs' opinions and the allowed visitors is set to the number allowed during the time of the survey wave. Secondly, in Section 4.2 the visitors measure is further explored. Here, an experiment is performed to explore different effects as a result of varying the allowed number of visitors. For each of these experiments, the experiment is described and a hypothesis is given, as well as the results of that experiment.

Finally, Section 4.3 describes a parameter sweep on the importances of the HUMAT population.

## 4.1 Experiments with RIVM data initializations

### 4.1.1 Experiment description

A number of experiments were performed using the different initializations of opinions by means of the RIVM survey data. In these experiments, all the adjustable parameters are set to the values described in Chapter 3 (including repulsion effects and HUMAT importances drawn from a normal distribution). For every wave of the survey, the HUMATs are initialized using the distribution of opinions of that particular wave, according to Table 3.1. The manner in which the opinions are initialized is described in Section 3.2.1 step 3. The number of allowed visitors per day is set to that of the government policy during that particular wave.

Two questions of interest for these experiments are:

1. *How does the distribution of opinions change over 100 days, given the different opinion initializations by the RIVM survey data?*

2. *How does the amount of active contact between agents change over 100 days, given the different opinion initializations by the RIVM survey data?*

In order to answer these questions, the model is run for 100 days for each RIVM initialization. Every day of the simulation, both the opinions of all 100 HUMATs and the number of active contacts are measured. The choice to test for 100 days comes from the fact that we are not necessarily interested in a final equilibrium after years of lockdown, but more in the process of change within a limited time.

### 4.1.2 Hypotheses

1. For the opinions, we expect to see a strong effect from the allowed number of visitors on the change and distribution of opinions, where a stricter measure (i.e. fewer allowed visitors) will lead to a higher decrease of the HUMATs' support for the policy than a less stringent measure.

   Moreover, the initialization of opinions plays a role in the fact that the model is run for 100 days, such that a population of HUMATs initialized with a higher average opinion (i.e. more support) regarding the visitors measure might end up with a higher average opinion after 100 days, given the same number of allowed visitors, than a population that is initialized with a lower average opinion. If we would run both initializations until the model converges, both initial situations would end up at a similar average opinion.

2. Regarding the amount of contact, due to HUMATs with the *no-contact* behaviour aiming to adhere to the rule, we expect to see a peak around the allowed number of visitors every day. However, in situations where the support decreases, more HUMATs will choose the *contact* behaviour, in which they disregard following the visitors measure. In those cases, such a peak might be less emphasized and the distribution of contacts may vary more. For the same reason, we expect the average number of daily contacts to increase as support for the visitors measure decreases.

| **Survey Wave and Date** | **Vis/day** | *Geen mening* | *Helemaal niet* | *Niet* | *Neutraal* | *Wel* | *Helemaal wel* |
|---|---|---|---|---|---|---|---|
| **6**: 19-23 aug 2020 | 6 | 0.9% | 4% | 7.3% | 11.8% | 27.9% | 48.1% |
| **7**: 30 sep - 4 oct 2020 | 4 | 0.5% | 3.1% | 7.4% | 11.9% | 30.6% | 46.5% |
| **8**: 11-15 nov 2020 | 2 | 0% | 5.8% | 10.5% | 13.7% | 28.9% | 41.1% |
| **9**: 30 dec 2020 - 3 jan 2021 | 2 | 0% | 3.3% | 6.6% | 10.9% | 30.7% | 48.5% |
| **10**: 10-14 feb 2021 | 1 | 0% | 9.2% | 18% | 17.1% | 27.2% | 28.5% |
| **11**: 24-28 mar 2021 | 1 | 0% | 10.4% | 23% | 19.3% | 25.3% | 22% |

Table 4.1: This is a replicate of Table 3.1, which is placed here as a mnemonic for the reader such that the results in Section 4.1.3 can be related to it. A more extensive description can be found in the original table.

### 4.1.3 Results

The results of the experiments can be found in Figures 4.1 to 4.12 on the following pages. For each of the six RIVM data initializations, there are two pages with results: Firstly, a page with results regarding the opinion changes for that wave. Secondly, a page regarding the changes in the amount of active contact for that wave. Both the pages for *opinions* and *contacts* results contain three figures.

**Opinion results:** For the opinion results, the figure on the upper left displays the average opinion of 100 HUMATs during a single run. The shaded area represents the standard deviation of the average opinion. The bottom figure illustrates a three-dimensional histogram of the distribution of opinions over time, starting with the initial distribution given in Table 4.1 for each wave. The upper right figure shows the average of the mean opinion of 100 HUMATs over 100 runs, which can be used to compare how a single run relates to the average of a number of runs. Here the shaded area represents the standard deviation between the mean opinion of different runs.

**Contacts results:** For the contact results, the figure on the top illustrates a three-dimensional histogram representing the distribution of the number of active contacts HUMATs have per day. The figure on the bottom right displays the same histogram as a perspective from above. In the bottom left figure, the green bars show the total number of contacts the HUMATs have per day and the red line results from a smoothing function, to display the pattern of changes in contact over time.

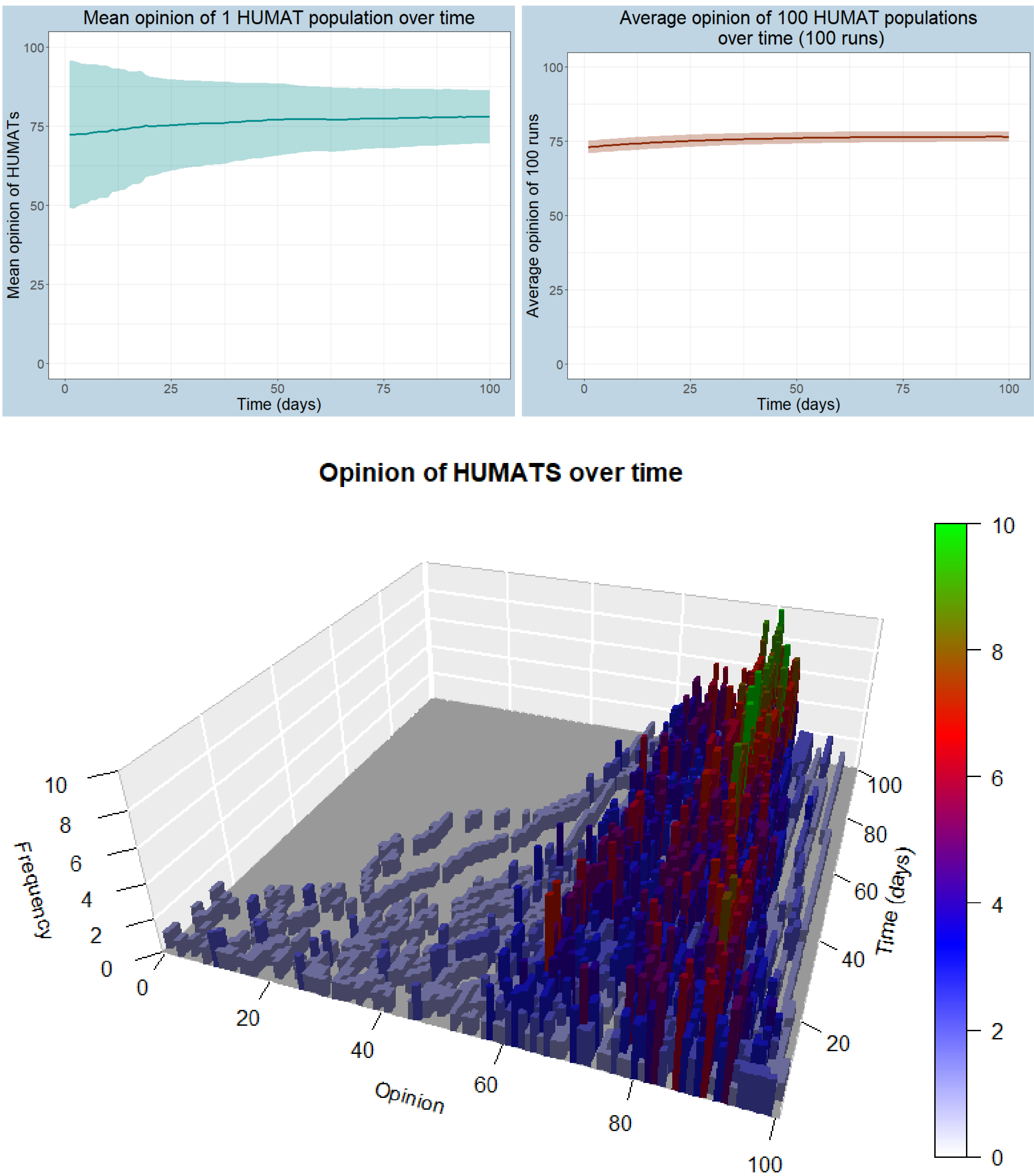



Figure 4.1: **Wave 6 - 19-23 aug 2020 - 6 visitors per day allowed - *Opinions*:**
Upper left: Average opinion of 100 HUMATs over 100 days. Upper right: Average of 100 runs of the mean opinion of 100 HUMATs over 100 days. Bottom: 3D histogram of the distribution of opinions over 100 days.

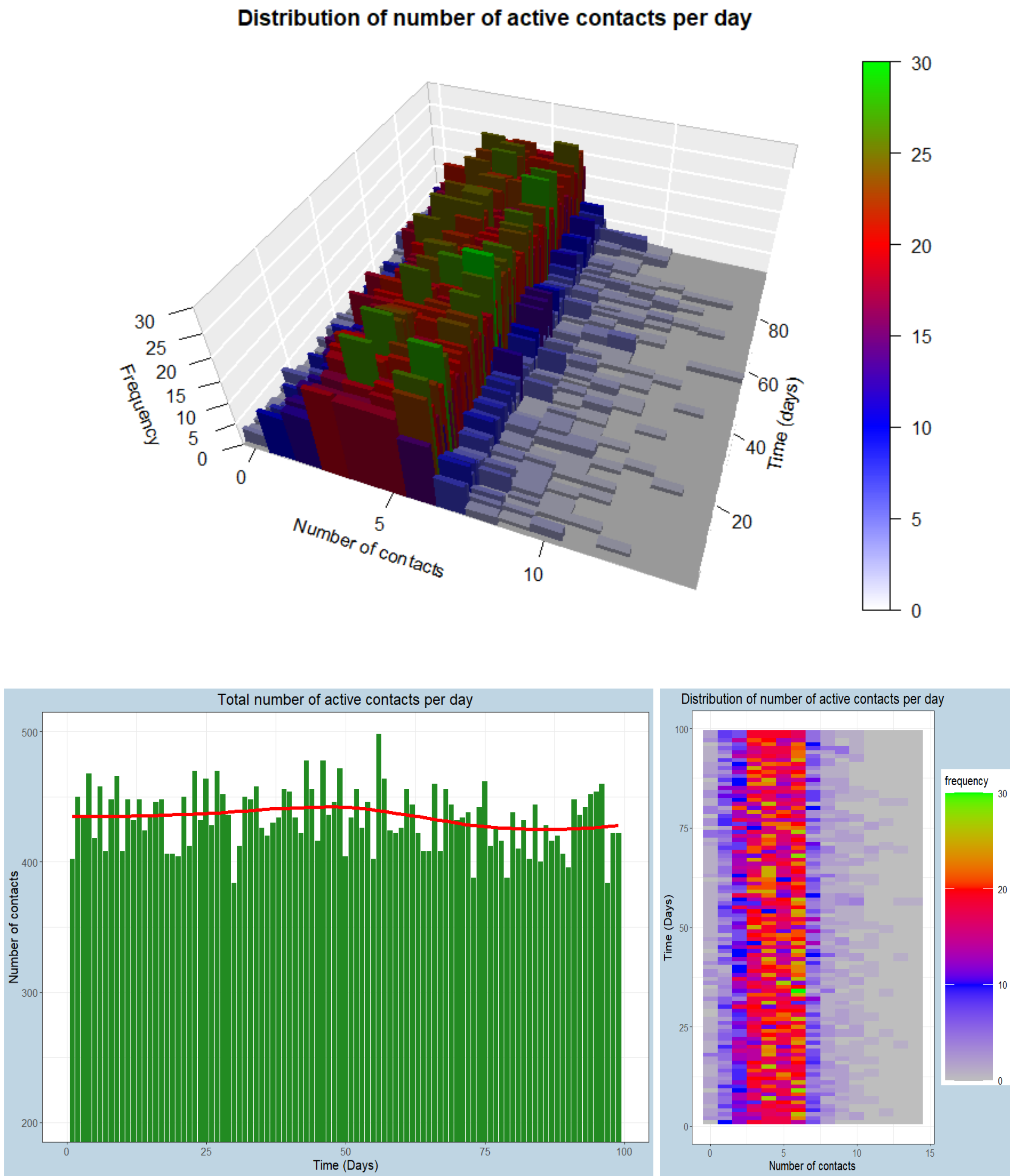



Figure 4.2: **Wave 6 - 19-23 aug 2020 - 6 visitors per day allowed - *Contacts*:**
Top: 3D histogram of the distribution of the number of active contacts HUMATs have per day. Bottom right: displays the same histogram as a perspective from above. Bottom left: The total number of contacts the HUMATs have per day.

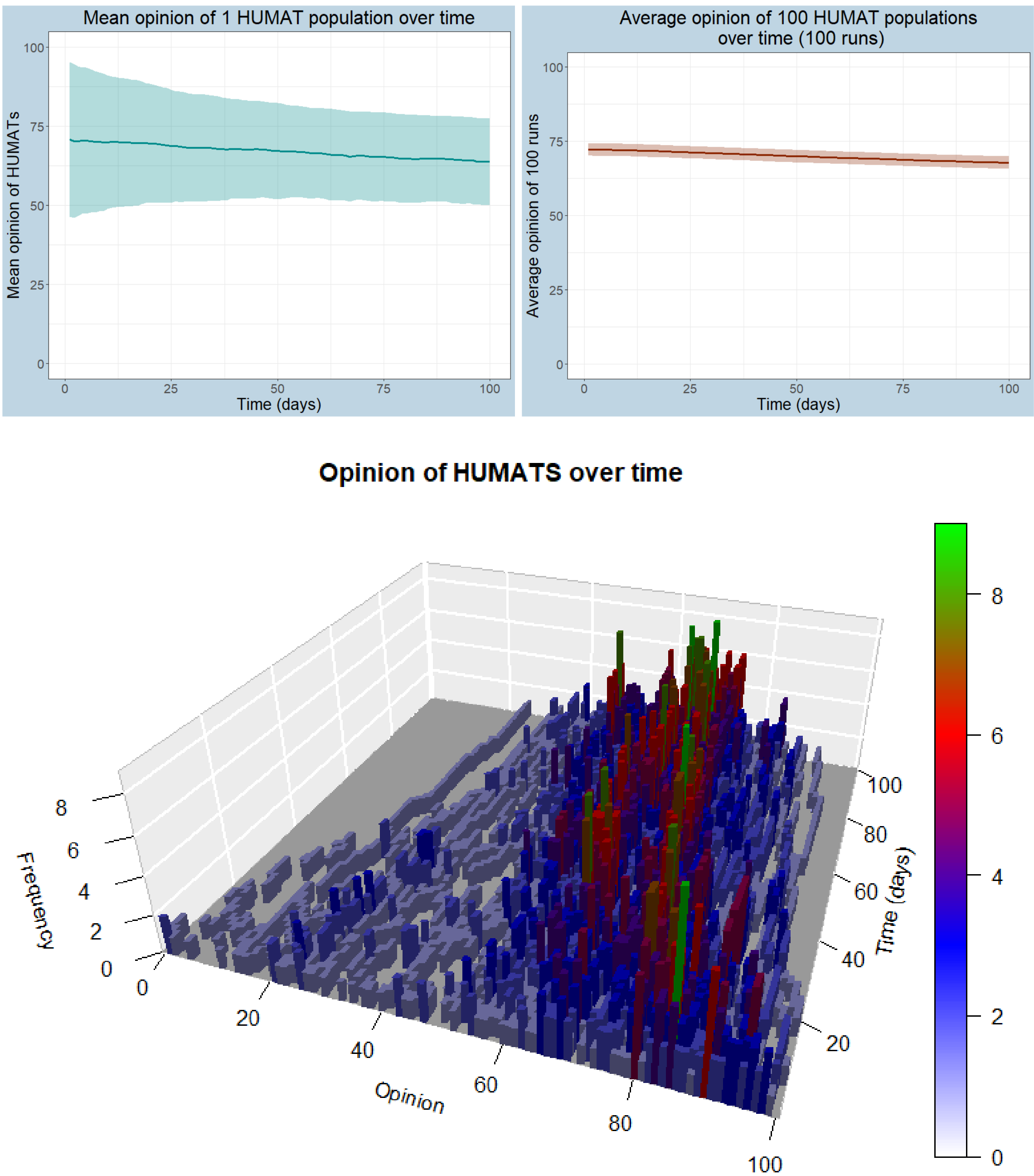
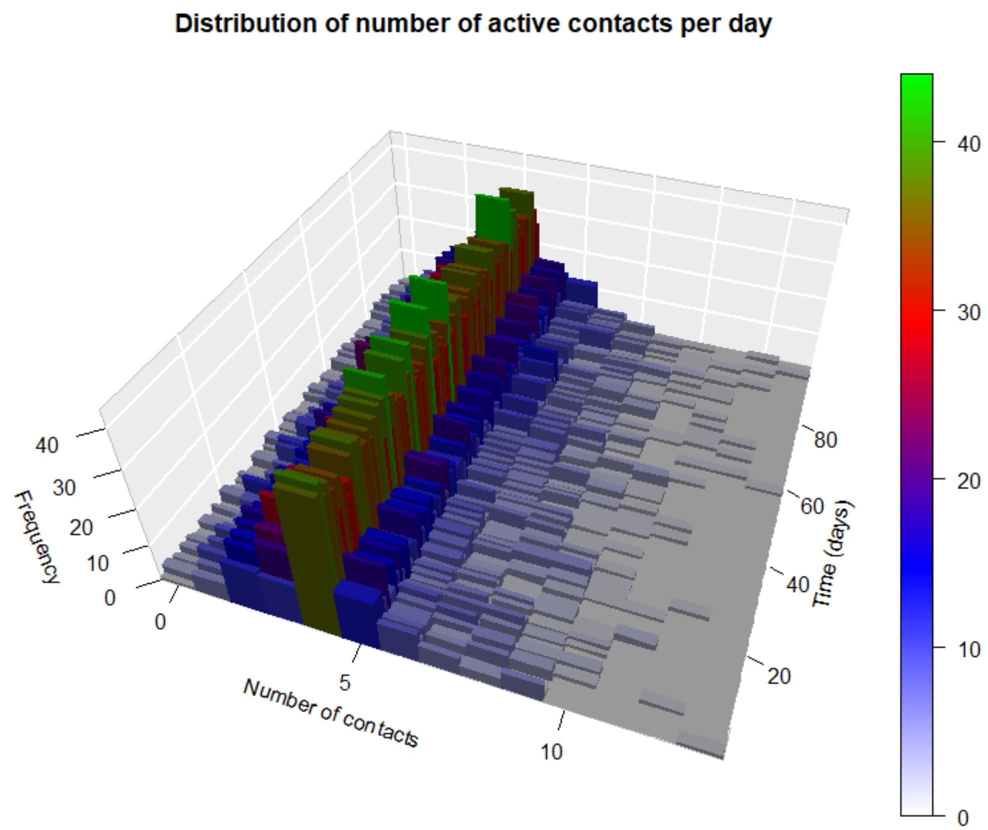



Figure 4.3: **Wave 7 - 30 sep - 4 oct 2020 - 4 visitors per day allowed - *Opinions*:** Upper left: Average opinion of 100 HUMATs over 100 days. Upper right: Average of 100 runs of the mean opinion of 100 HUMATs over 100 days. Bottom: 3D histogram of the distribution of opinions over 100 days.



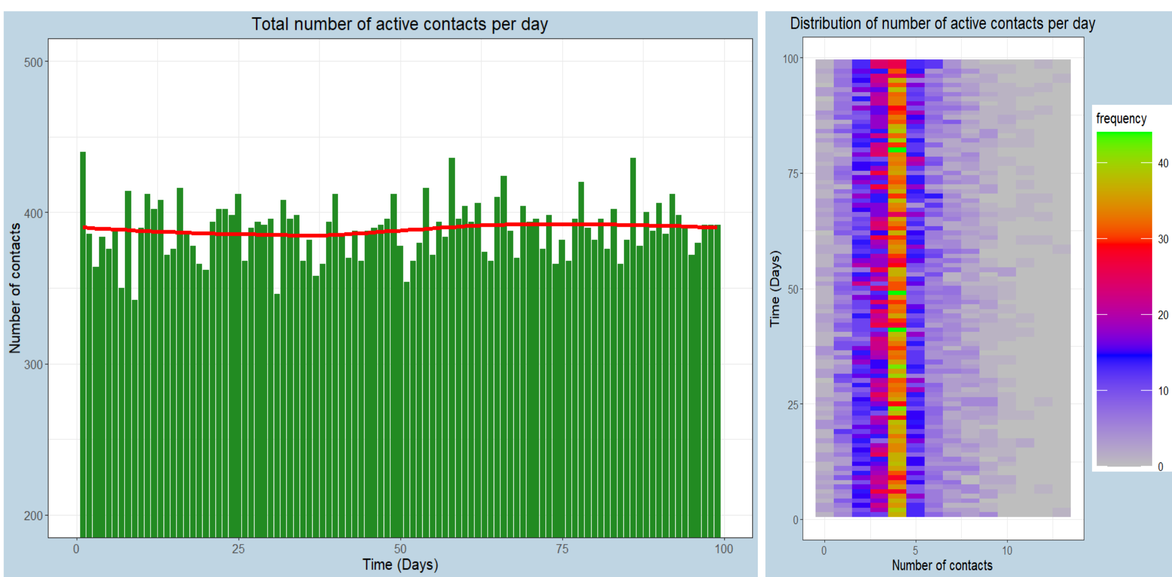




Figure 4.4: **Wave 7 - 30 sep - 4 oct 2020 - 4 visitors per day allowed - *Contacts*:**
Top: 3D histogram of the distribution of the number of active contacts HUMATs have per day. Bottom right: displays the same histogram as a perspective from above. Bottom left: The total number of contacts the HUMATs have per day.

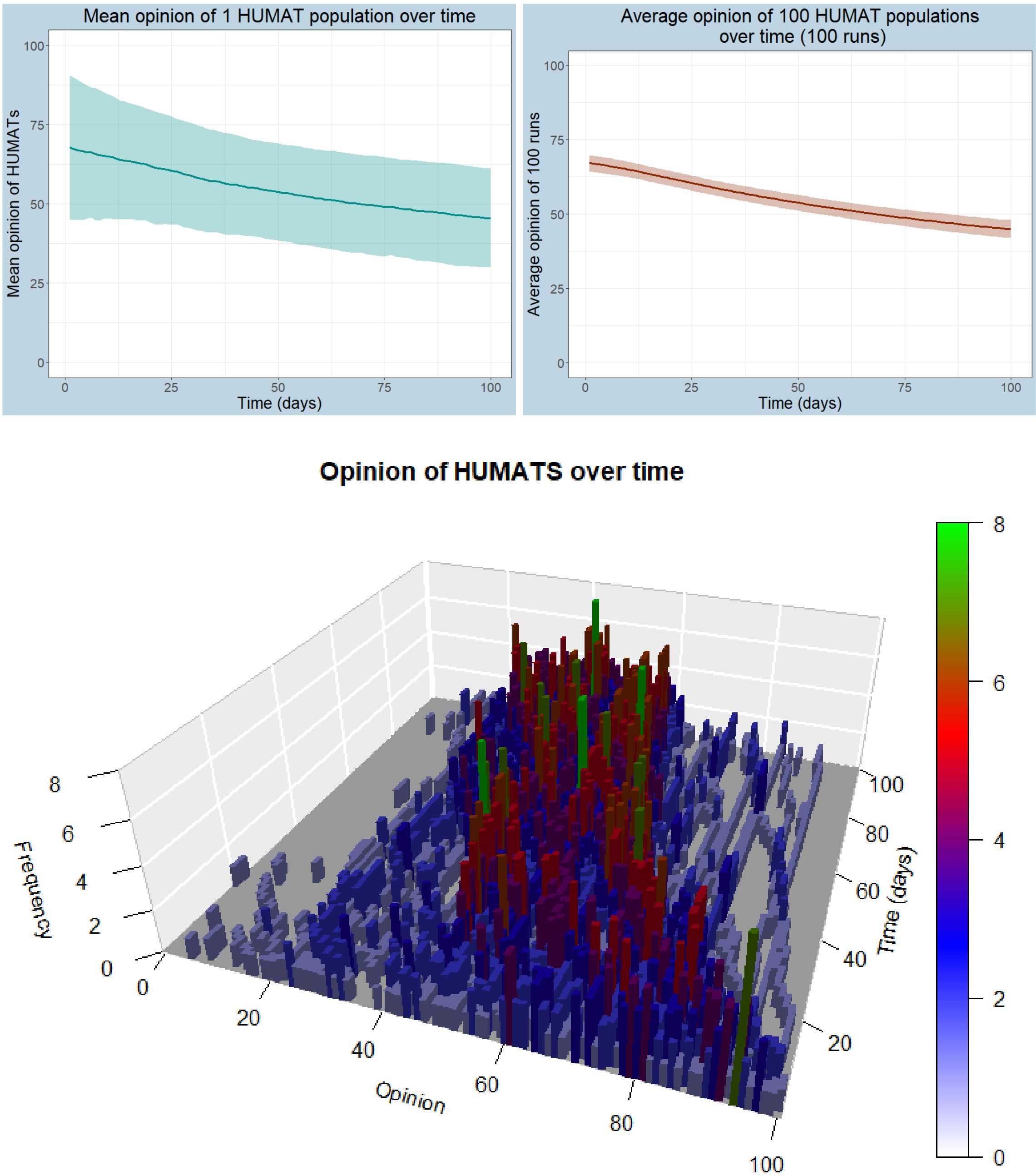



Figure 4.5: **Wave 8 - 11-15 nov 2020 - 2 visitors per day allowed - *Opinions*:**
Upper left: Average opinion of 100 HUMATs over 100 days. Upper right: Average of 100 runs of the mean opinion of 100 HUMATs over 100 days. Bottom: 3D histogram of the distribution of opinions over 100 days.

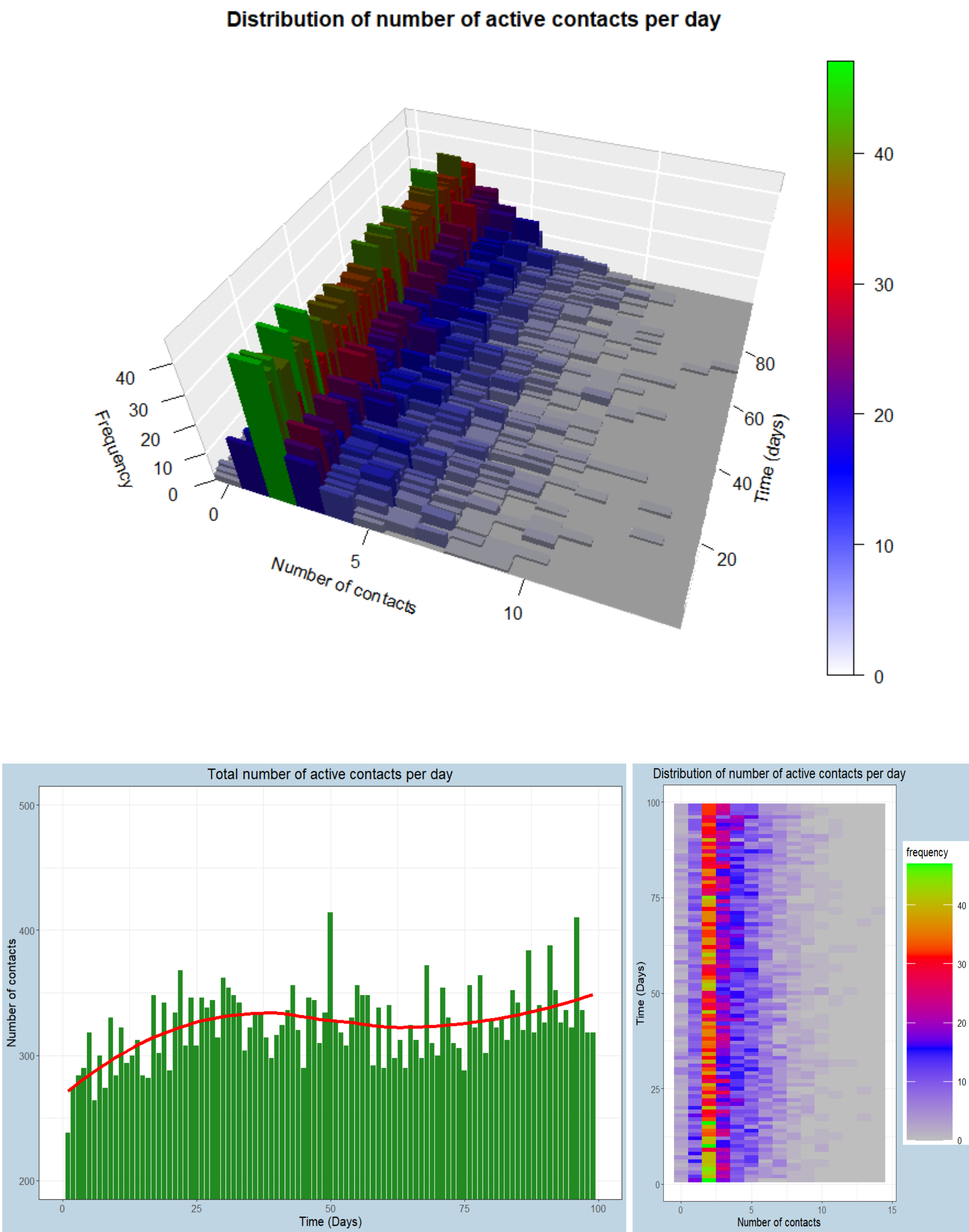



Figure 4.6: **Wave 8 - 11-15 nov 2020 - 2 visitors per day allowed -** ***Contacts*****:**
Top: 3D histogram of the distribution of the number of active contacts HUMATs have per day. Bottom right: displays the same histogram as a perspective from above. Bottom left: The total number of contacts the HUMATs have per day.

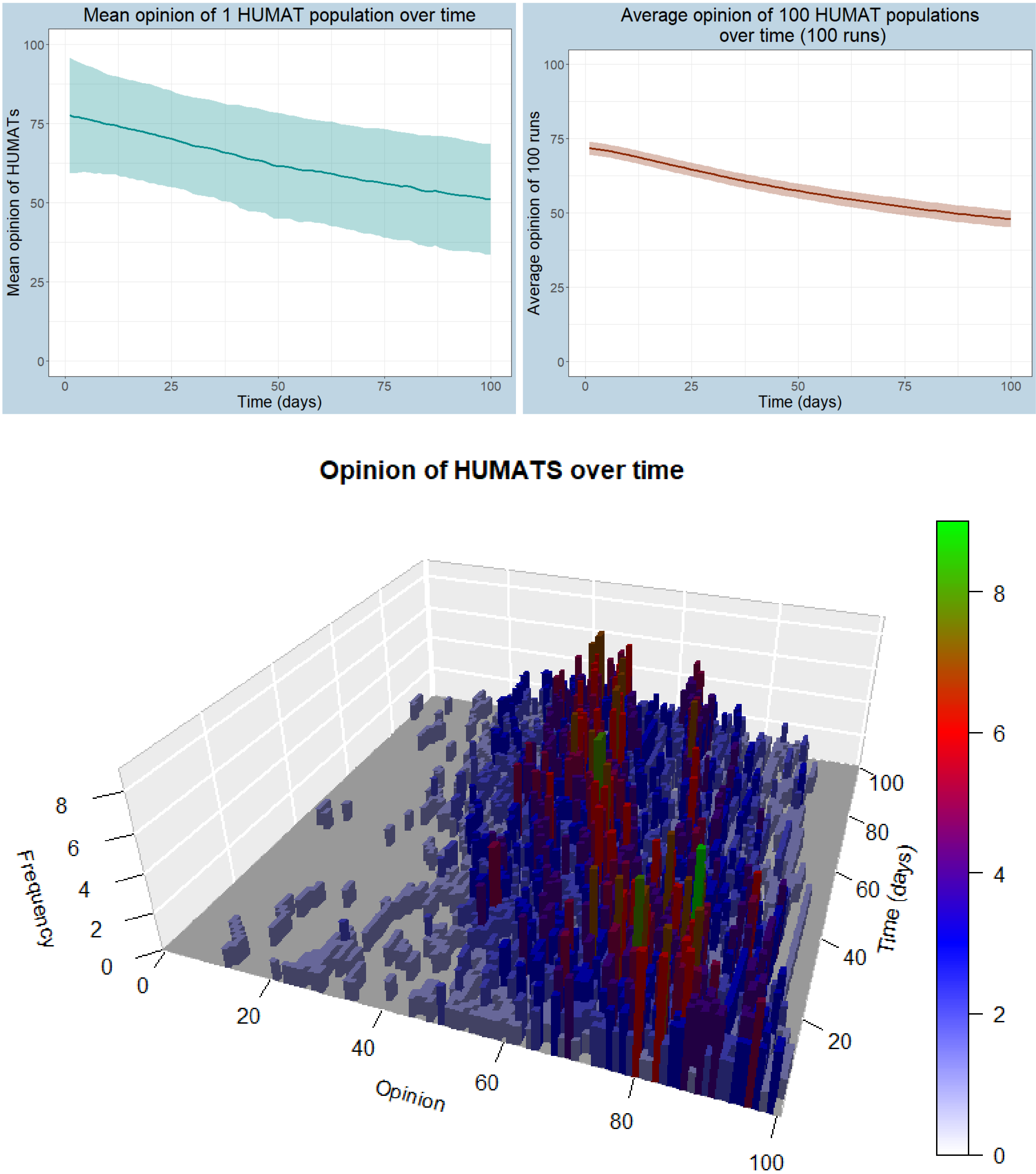



Figure 4.7: **Wave 9 - 30 dec 2020 - 3 jan 2021 - 2 visitors per day allowed - *Opinions*:** Upper left: Average opinion of 100 HUMATs over 100 days. Upper right: Average of 100 runs of the mean opinion of 100 HUMATs over 100 days. Bottom: 3D histogram of the distribution of opinions over 100 days.

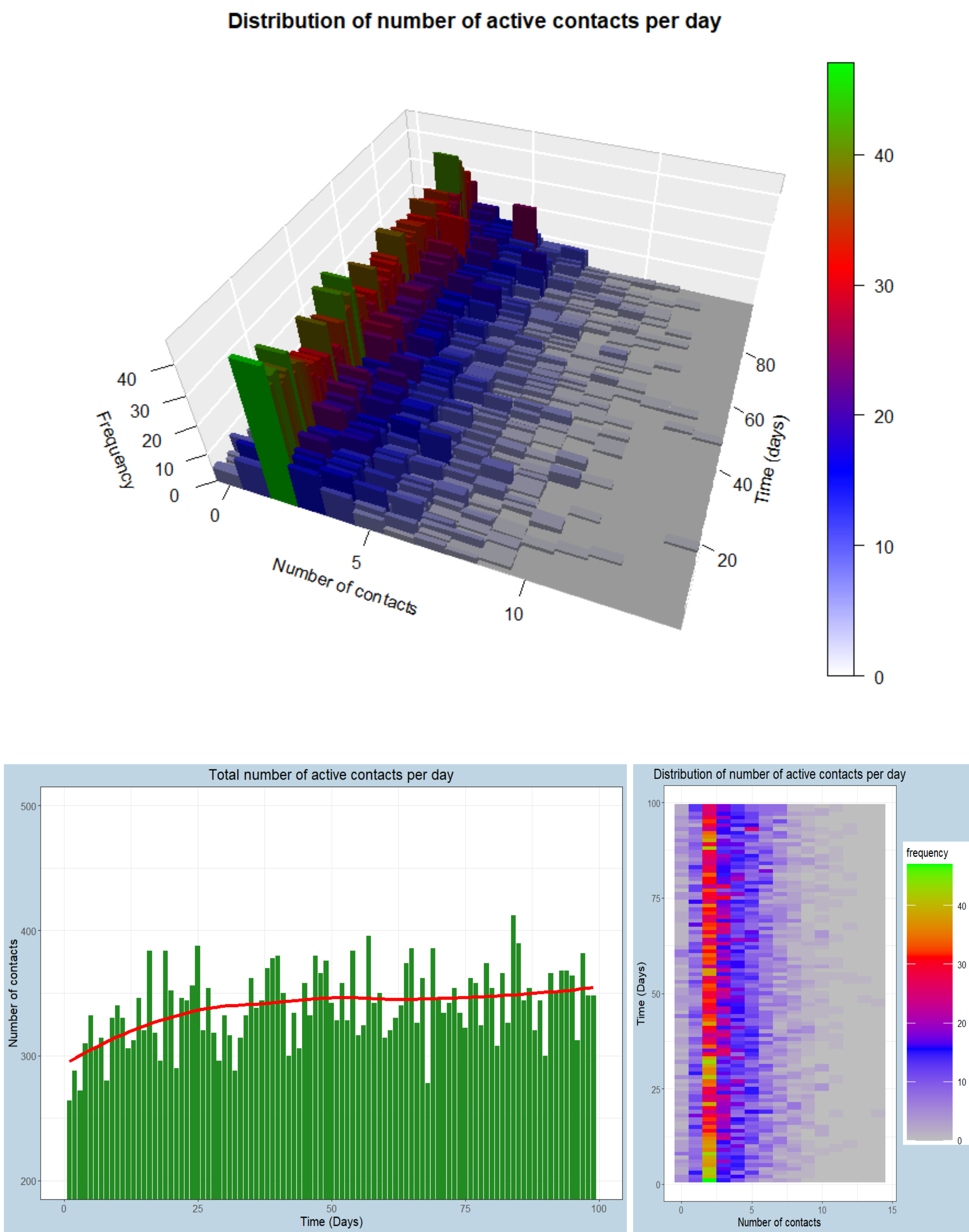



Figure 4.8: **Wave 9 - 30 dec 2020 - 3 jan 2021 - 2 visitors per day allowed -** ***Contacts*****:**
Top: 3D histogram of the distribution of the number of active contacts HUMATs have per day. Bottom right: displays the same histogram as a perspective from above. Bottom left: The total number of contacts the HUMATs have per day.

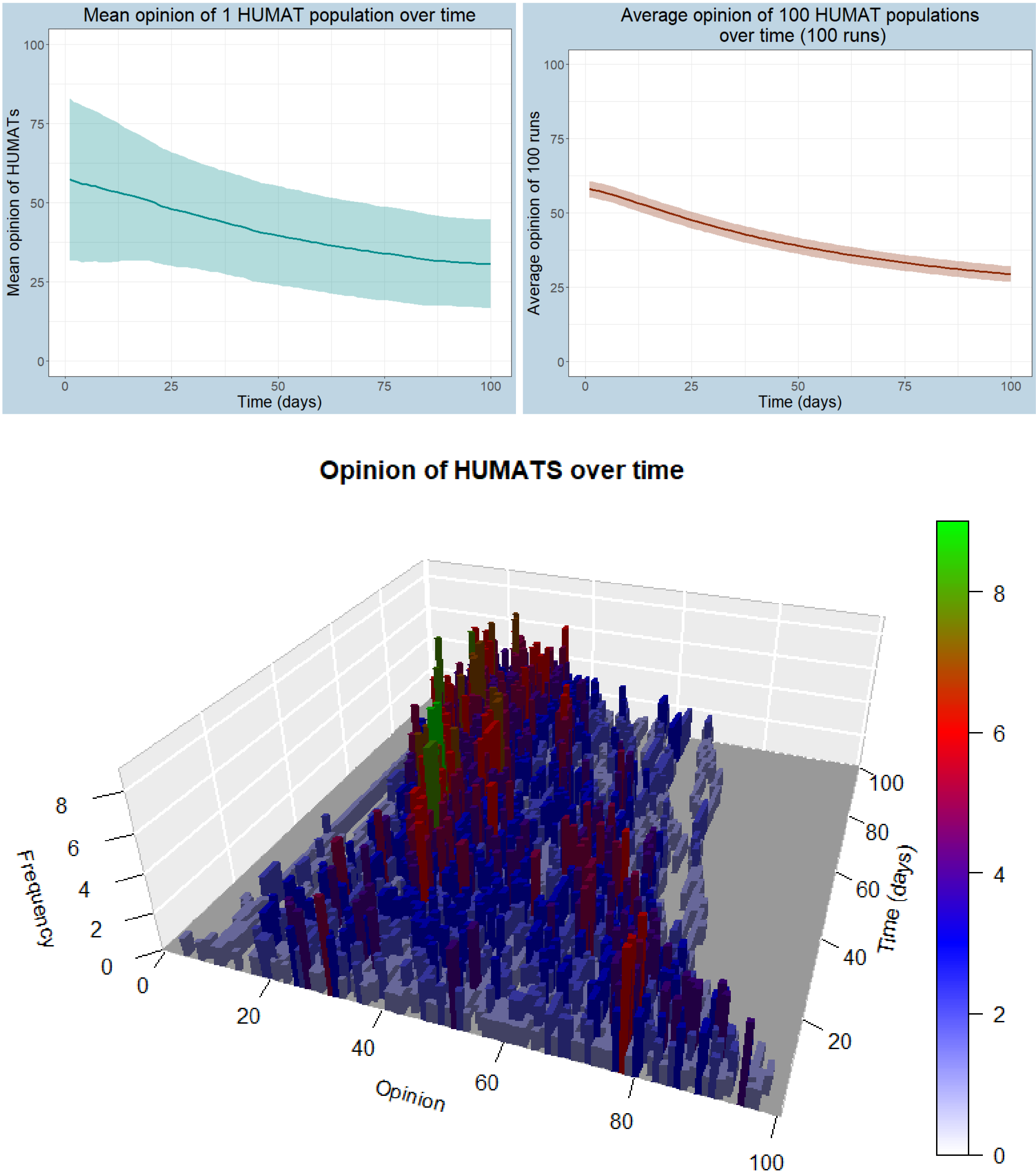



Figure 4.9: **Wave 10 - 10-14 feb 2021 - 1 visitors per day allowed - *Opinions*:**
Upper left: Average opinion of 100 HUMATs over 100 days. Upper right: Average of 100 runs of the mean opinion of 100 HUMATs over 100 days. Bottom: 3D histogram of the distribution of opinions over 100 days.

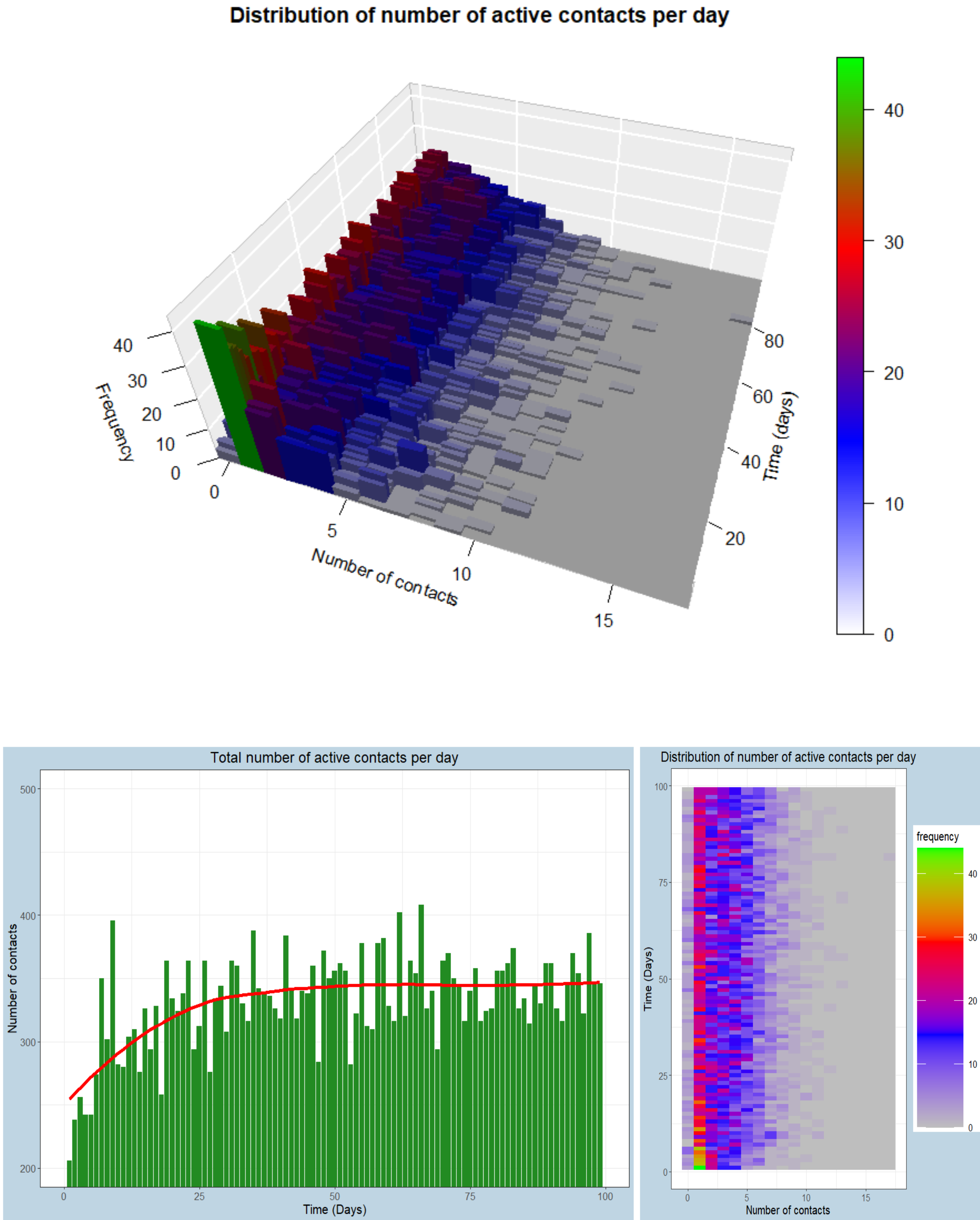



Figure 4.10: **Wave 10 - 10-14 feb 2021 - 1 visitors per day allowed -** ***Contacts*****:**
Top: 3D histogram of the distribution of the number of active contacts HUMATs have per day. Bottom right: displays the same histogram as a perspective from above. Bottom left: The total number of contacts the HUMATs have per day.

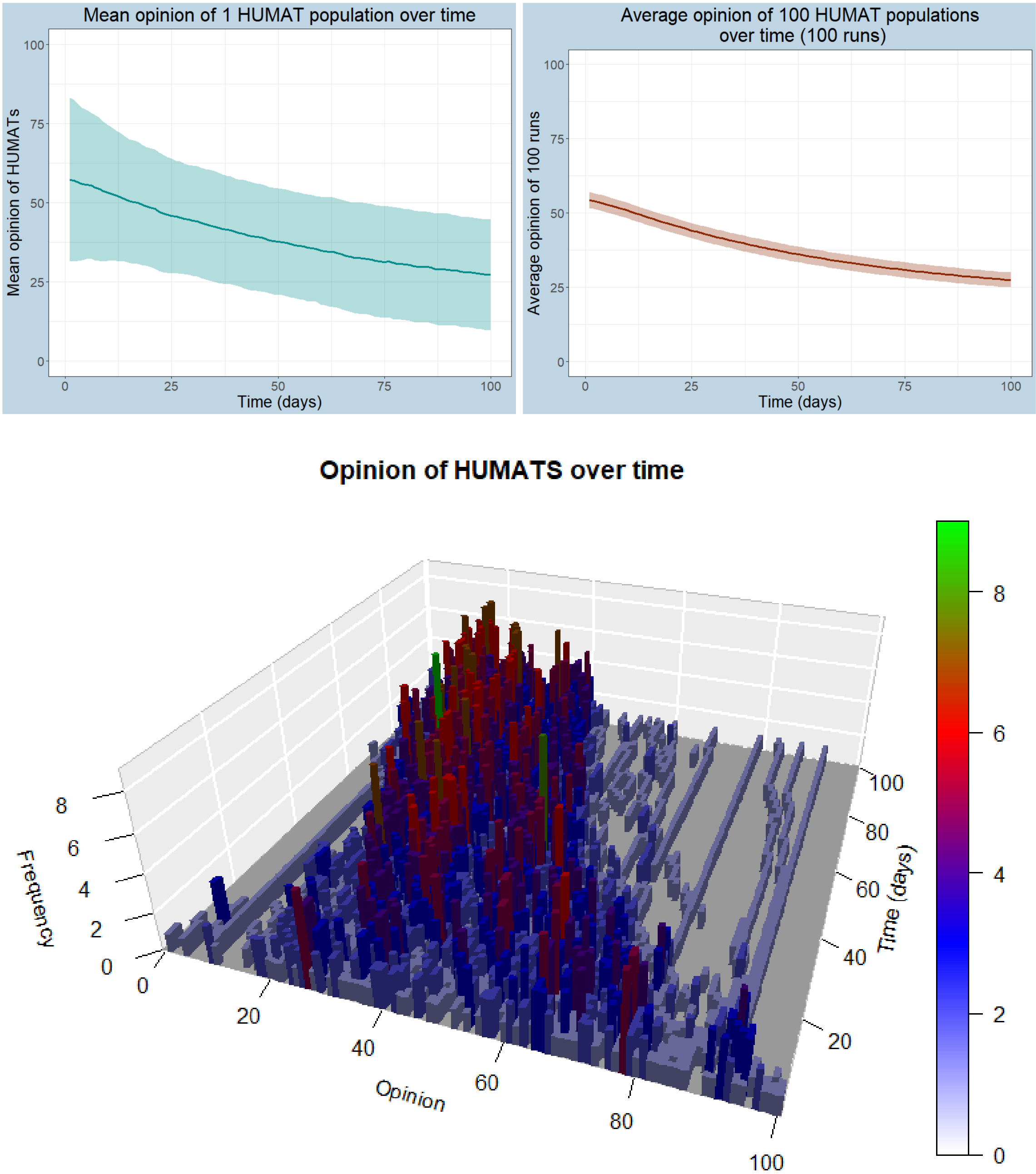
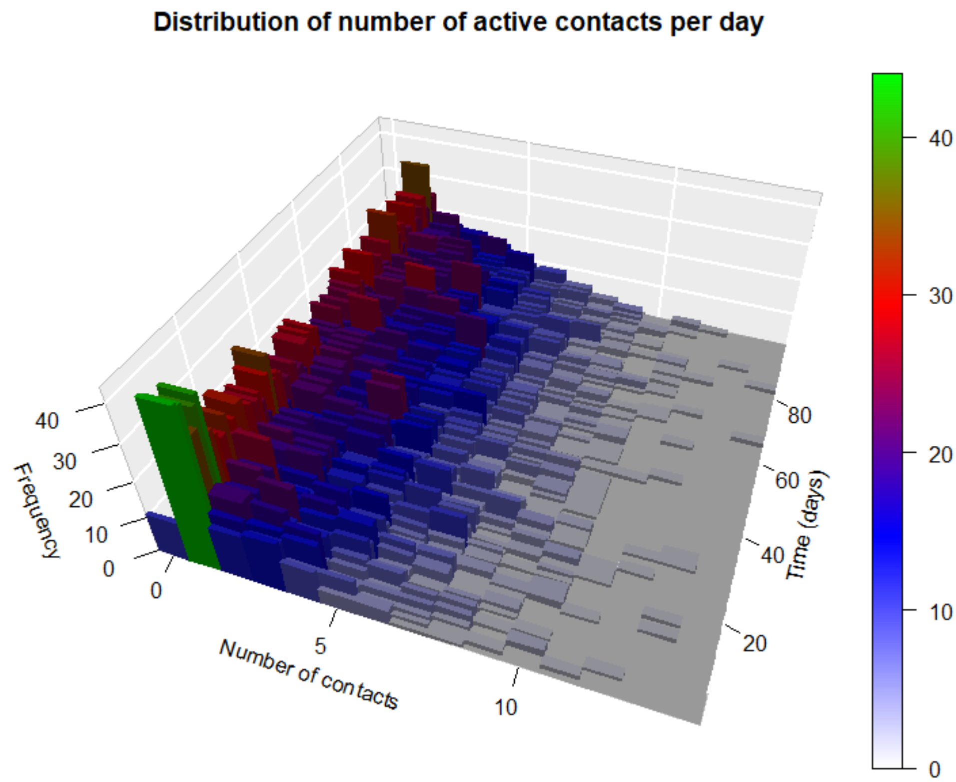



Figure 4.11: **Wave 11 - 24-28 mar 2021 - 1 visitors per day allowed - *Opinions*:**
Upper left: Average opinion of 100 HUMATs over 100 days. Upper right: Average of 100 runs of the mean opinion of 100 HUMATs over 100 days. Bottom: 3D histogram of the distribution of opinions over 100 days.



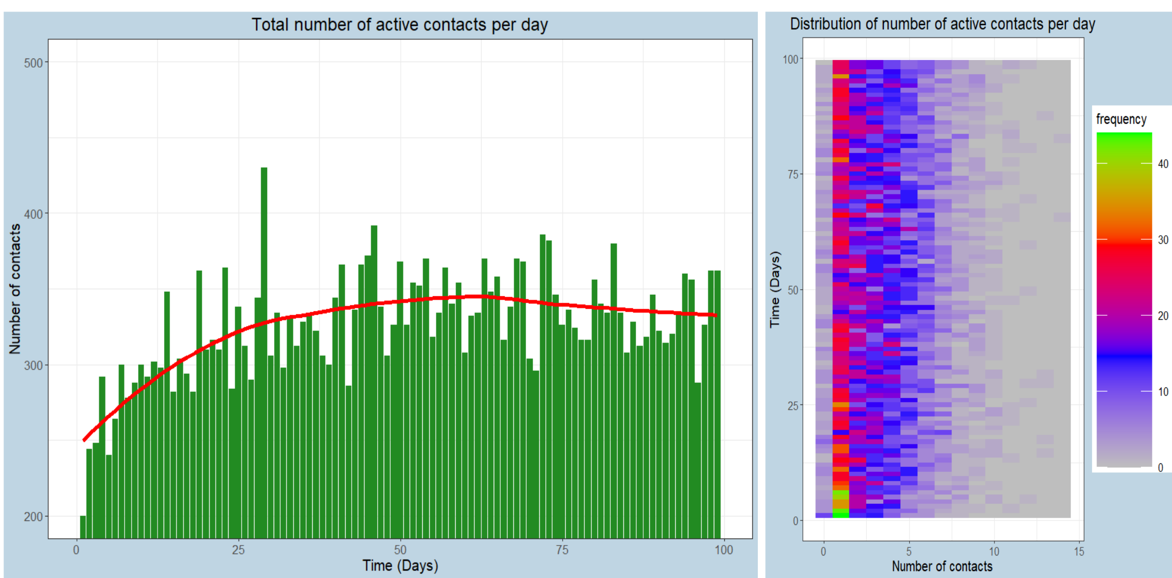




Figure 4.12: **Wave 11 - 24-28 mar 2021 - 1 visitors per day allowed -** ***Contacts*****:**
Top: 3D histogram of the distribution of the number of active contacts HUMATs have per day. Bottom right: displays the same histogram as a perspective from above. Bottom left: The total number of contacts the HUMATs have per day.

## 4.2 Exploring the effects of different visitors measures

### 4.2.1 Experiment description

In this experiment, the effects of varying the strictness of the visitors measure are explored. All the adjustable parameters are set to the values described in Chapter 3. In contrast to the experiments described in Section 4.1, here the HUMATs are initialized with opinions drawn from a random-uniform distribution every run. Consequently, the mean opinion of the population will be approximately 50 at the start of every run. The varied parameter for this experiment is the allowed number of visitors per day, which is varied from 1 to 10. The aim of this experiment is to explore the effects of the visitors measure on three phenomena:

- The change of opinions of the HUMAT population over time,
- the number of contacts the HUMATs have, and
- the behaviour the HUMATs choose to follow.

Moreover, we are interested in the coherence between these phenomena. Therefore, the main questions of interest for this experiment are:

1. *How do differences in the strictness of the visitors measure affect the HUMATs' support for the measure (change in opinion) over time?*
2. *How do differences in the strictness of the visitors measure affect the number of contacts the HUMATs have?*
3. *How do differences in the strictness of the visitors measure affect the behaviour HUMATs choose to follow?*

In order to answer these questions, for each number of allowed daily visitors (1-10), the model is run for 100 times, in which a population of 100 HUMATs is investigated for 100 days. We measure the opinion of all HUMATs every day, as well as the number of contacts the HUMATs have per day and the percentage of HUMATs with the *no-contact* behaviour.

### 4.2.2 Hypotheses

1. Similar to the hypothesis in Section 4.1.2, we expect a strong effect from the number of allowed visitors on the change and distribution of opinions, where a stricter measure (i.e. fewer allowed visitors) will lead to a higher decrease of the HUMATs' support for the policy than a less stringent measure.
2. For the contacts, we expect to see fewer contacts with stricter visitors measures. We expect the differences to be stronger between stricter visitors measures. More lenient measures could be closer to the experiential needs for the HUMATs, hence a lenient measure might not limit the HUMATs in satisfying these needs, leading to less emphasized differences than when the measure does limit the satisfaction of their needs.
3. For the same reason as discussed above, we expect fewer HUMATs to choose following the *no-contact* behaviour when the visitors measure is stricter.

Given these expectations, we expect to see coherence in the effect of changing the visitors measure on the three phenomena.

### 4.2.3 Results

The results of the experiments can be found on the following pages.

Figure 4.13 shows lines representing the average of the mean opinion of 100 HUMATs over 100 runs for each allowed number of visitors per day (depicted by the different colours). The shaded area represents the standard deviation from the average opinion of the 100 runs. Figure 4.14 shows bar plots of the mean opinion during a run and the mean final opinion. Here the error bars denote the standard deviation from the average opinion of the 100 runs.

Figure 4.15 shows two plots: a line plot representing the cumulative number of active contacts over time per HUMAT, averaged over the 100 runs and a bar plot illustrating the average number of active contacts over 100 days per HUMAT, both for each allowed number of visitors per day (depicted by the different colours).

Figure 4.16 shows bar plots regarding the mean percentage of HUMATs with the *no-contact* behaviour (i.e. with the aim to follow the measure) during 100 days and on the final day.

Finally, Figure 4.17 shows a bar plot in which the mean opinion on the final day (in red) and number of contacts per HUMAT over 100 days (in green) from Figures 4.14 and 4.15 are shown in conjunction.

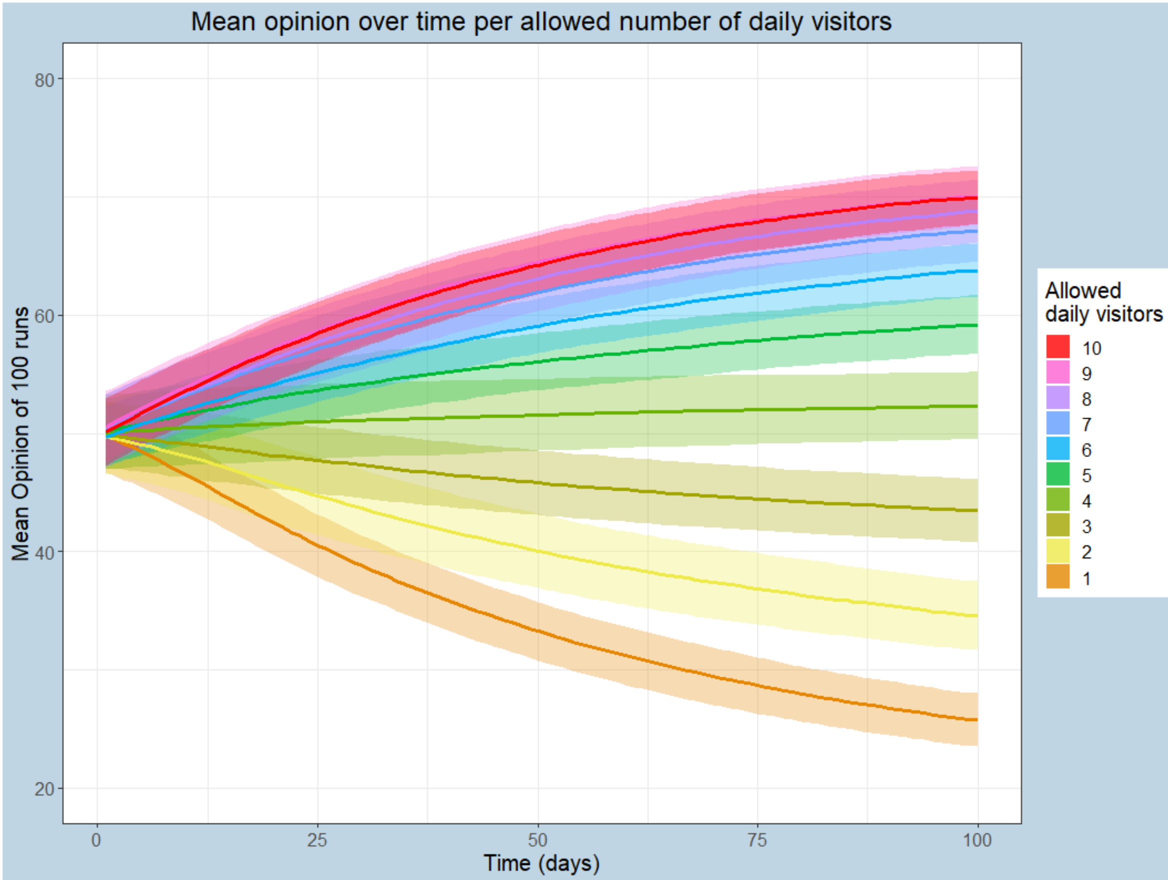



Figure 4.13: This figure shows the average support over 100 days for the visitors measure for different allowed numbers of visitors for 100 runs, given a random uniform initial distribution of opinions. The different colours depict the different allowed numbers of daily visitors. The shaded areas represent the standard deviation from the mean opinion of the 100 runs.

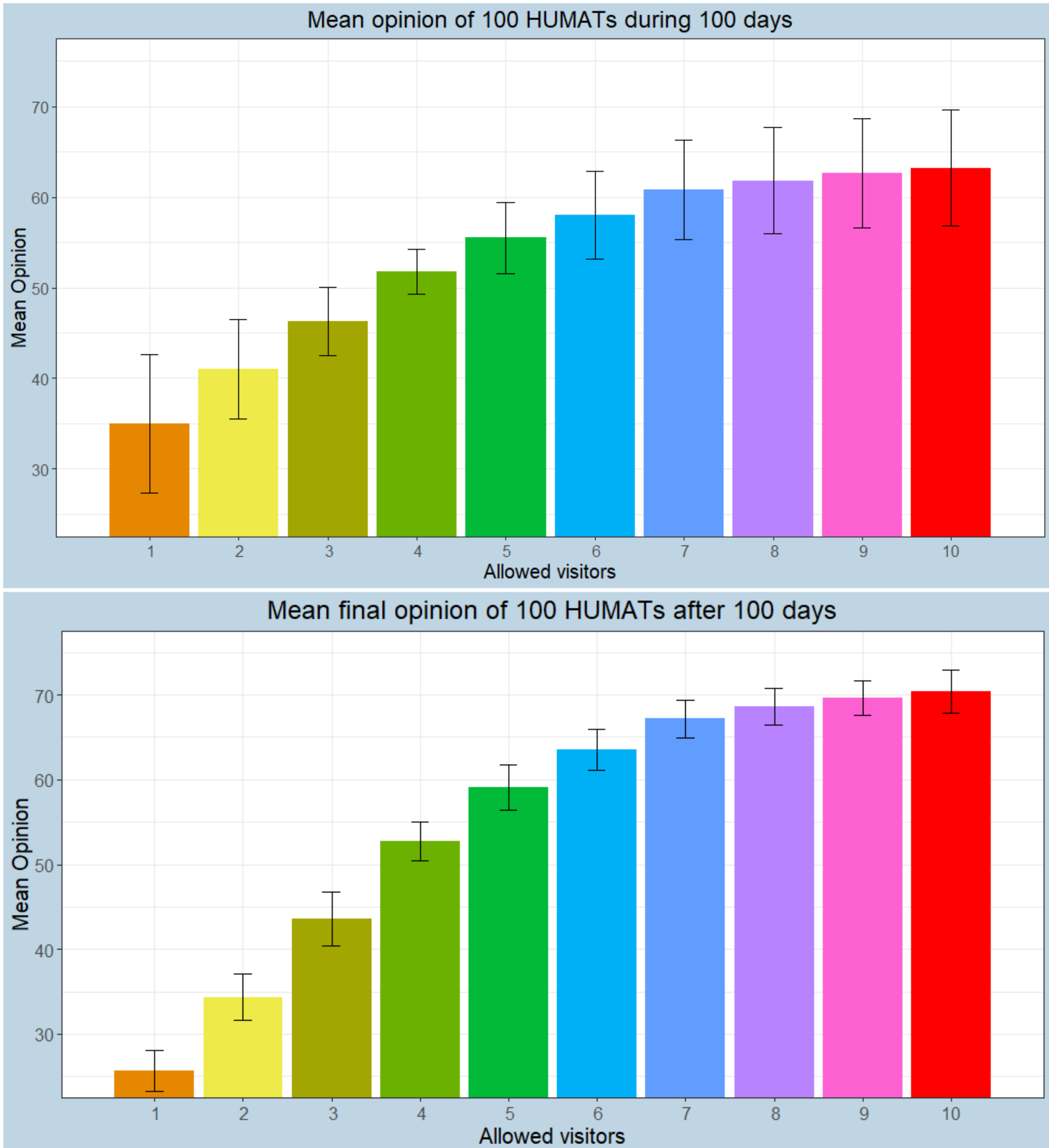



Figure 4.14: In this figure, the top plot shows bars representing the mean opinion during 100 days of a run and the bottom plot shows the mean final opinion after 100 days. The error bars denote the standard deviation from the average opinion of the 100 runs.

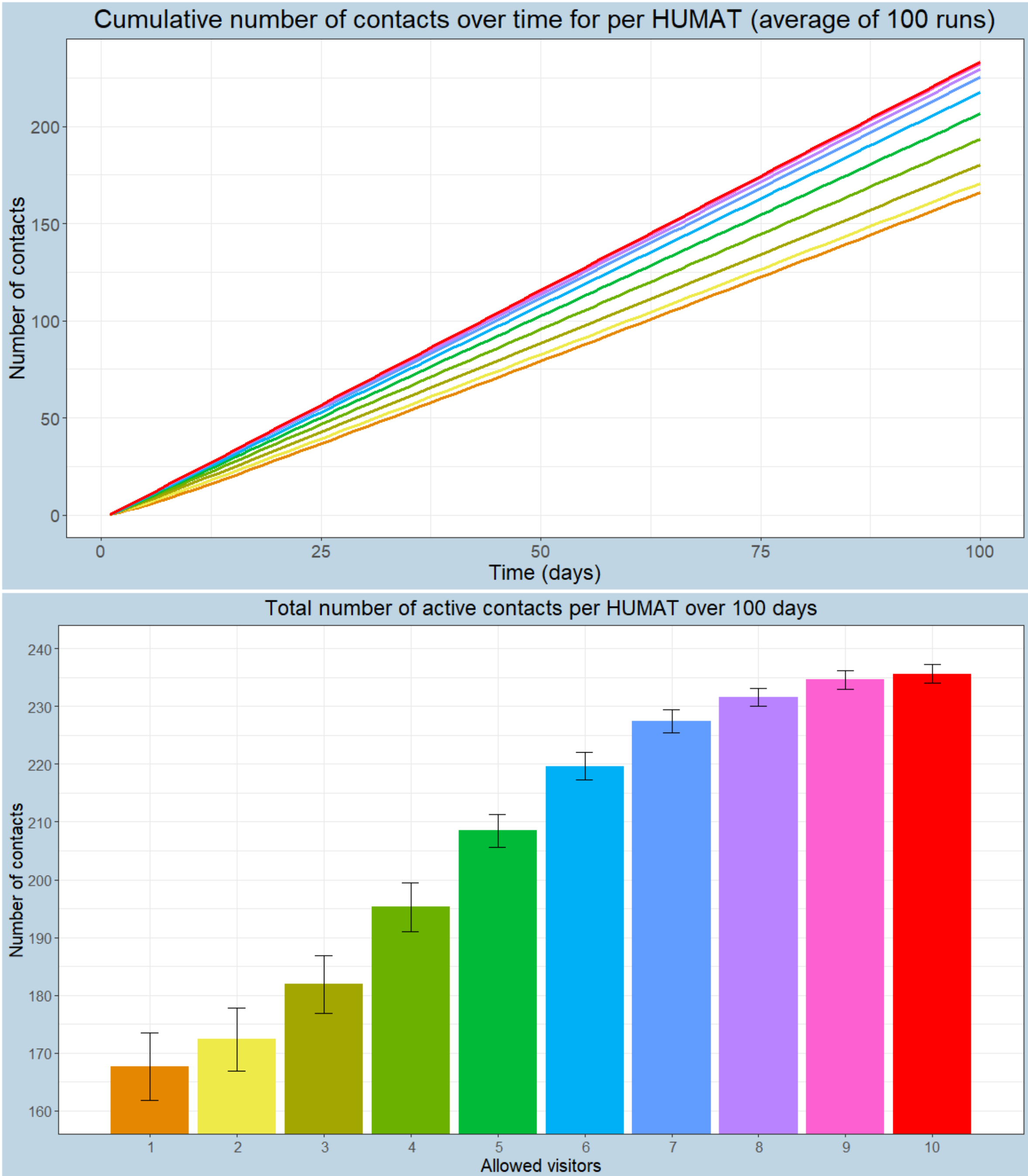



Figure 4.15: In this figure, the top (line) plot represents the cumulative number of active contacts over time per HUMAT, averaged over the 100 runs. The different colours depict the different allowed numbers of daily visitors (which colour denotes which can be extracted from the bottom bar plot). The bottom bar plot illustrates the average number of active contacts over 100 days per HUMAT, with the error bars showing the standard deviation from the average total number of contacts of the 100 runs.

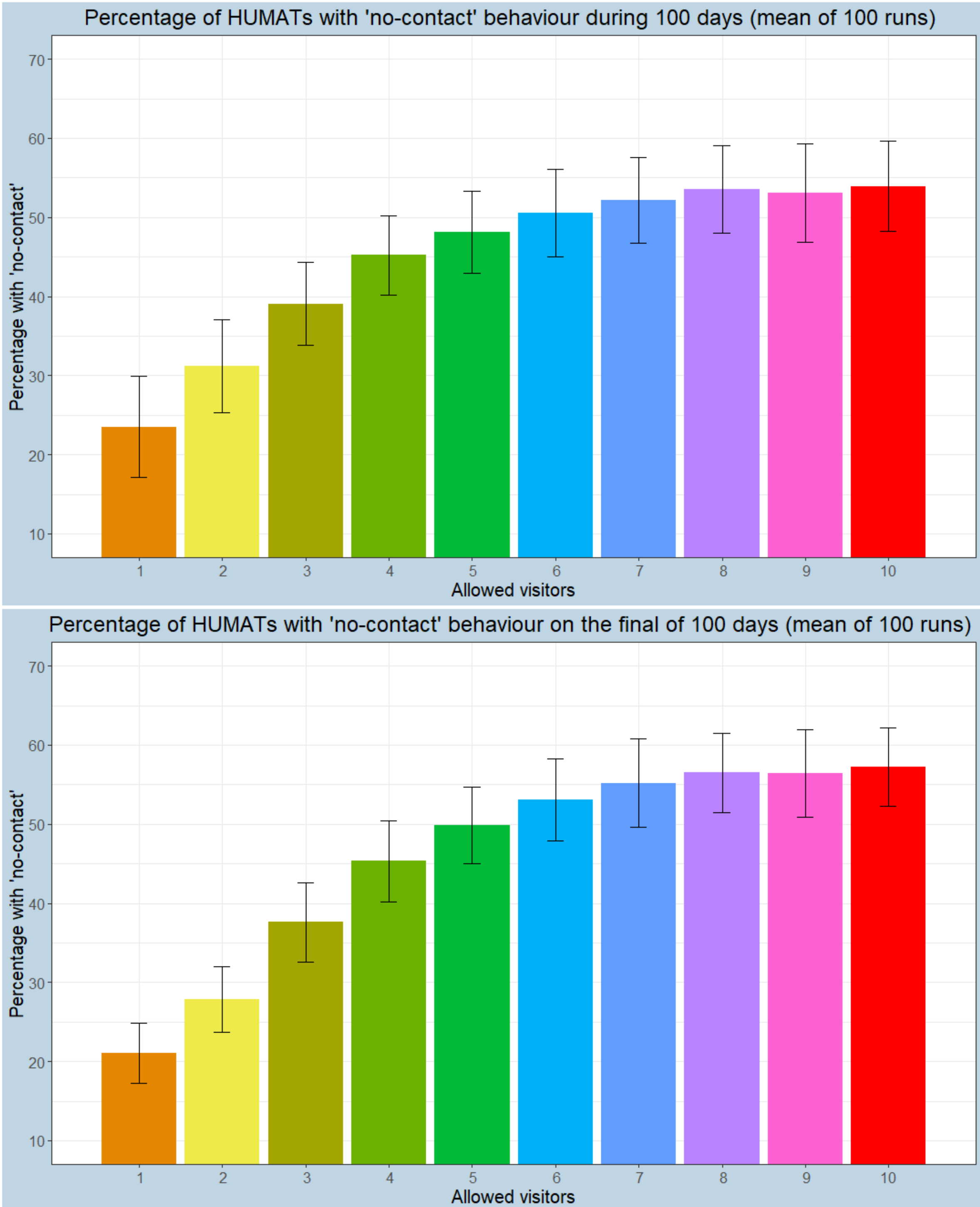



Figure 4.16: This figure shows two bar plots: The top plot shows the mean percentage of HUMATs with the *no-contact* behaviour during 100 days. The bottom plot shows the mean percentage of HUMATs with the *no-contact* behaviour on the final day. The error bars denote the standard deviation from the average percentage of HUMATs with the *no-contact* behaviour with of the 100 runs.

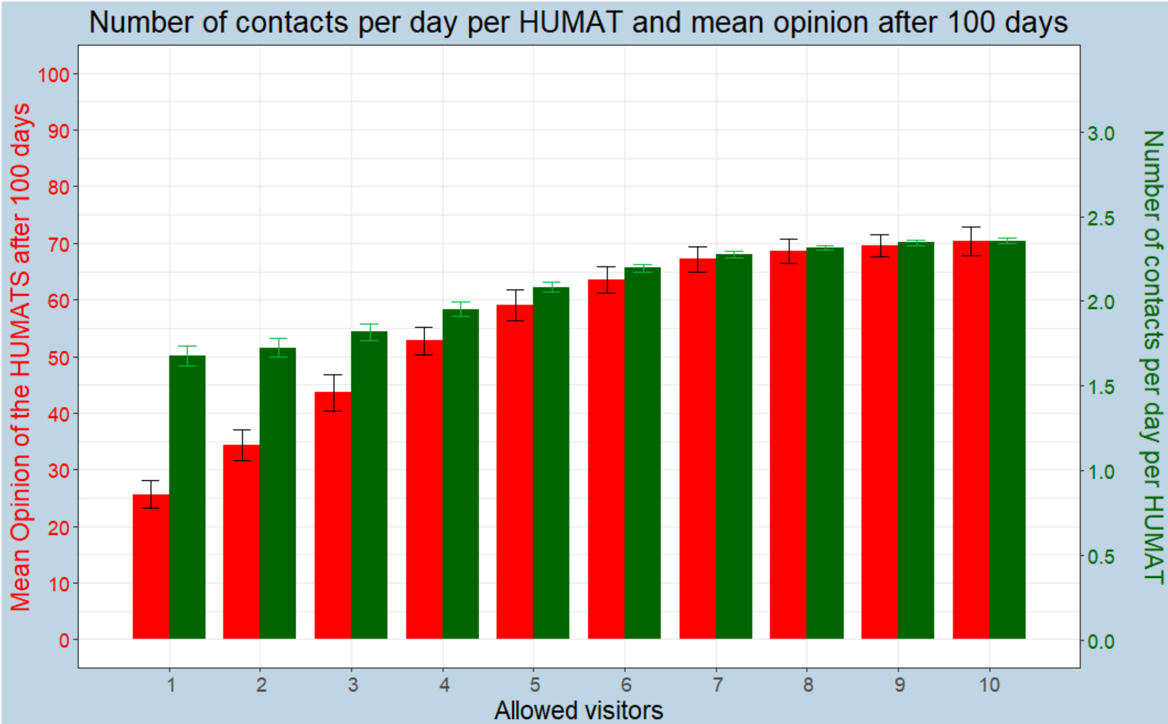



Figure 4.17: This figure shows a combination of the mean opinion on the final day (in red) and number of contacts per HUMAT per day (in green) from Figures 4.14 and 4.15. Note that each color has its own y-axis.

## 4.3 Importances parameter sweep

### 4.3.1 Experiment description

A parameter sweep was performed on the importances of the HUMAT population, in which experiments are run with different combinations of the Experiential Importance and Values Importance on different visitors measure strictnesses. More specifically, both the experiential and values importance are varied for the following six values: $[0, 0.2, 0.4, 0.6, 0.8, 1]$. The strictness of the visitors measure is varied for the values $[2, 4, 6]$. Consequently, in total there are $6 * 6 * 3 = 108$ different combinations of these parameters, which are all run 100 times. In each of these runs, four categories of variables are measured at the end of every day. These are the following:

- The average number of active contacts per HUMAT on that day,
- The average number of HUMATs that are in a dilemma on that day,
- The mean opinion on that day, and
- The standard deviation of the opinion on that day.

### 4.3.2 Results

The results of the parameter sweep are aggregated over the 100 runs and are displayed in Appendix B. Here, the results are distinguished into two sets, each with its own section:

1. The first set of results concerns the *mean values* for the aforementioned categories over the full run (e.g., the mean opinion value averaged over all days of a run) and are displayed in Section B.1.

   In Figures B.1 to B.3, a number of heatmaps can be found for the first set of results. The upper left heatmap, in blue, displays the average number of active contacts per day per HUMAT. The upper right heatmap, in red, displays the average number of dilemmas per day per HUMAT. The bottom left heatmap, in green, displays the mean opinion of the HUMAT population during the runs. The bottom right heatmap, in purple, displays the average standard deviation of the opinion during the runs.

2. The second set of results concerns the *final values* for the aforementioned categories (e.g., the mean opinion value at the final day of the run) and are displayed in Section B.2.

   In Figures B.4 to B.6, the heatmaps display the same categories in the respective configuration, but in contrast to Section B.1, here they consider the final values of each category.

# 5 | Discussion

This chapter firstly answers the research questions that were posed in Section 1.2, through the insights and results obtained in Chapters 2 to 4. Afterwards, it offers some suggestions and directions for future work, both improvements and extensions to the model. Finally, it discusses the relevance of the work done for this thesis both for ABM and in general and ends with a concluding section.

## 5.1 Research questions

1. *Can we create an agent-based model in which the interaction between the support for the Dutch COVID visitors measure and the need for social contact can be explored?*

   We believe the model that was developed captures some of the key elements of the interaction between the support for the Dutch COVID visitors measure and the need for social contact. The model appears to be stable, is relatively easy to understand and can easily be adapted or extended. Hence, we were able to create an agent-based model in which this interaction can be explored.

   (a) *Is the HUMAT framework (Antosz et al., 2019) a suitable cognitive framework to model different agent needs and decision making for this case?*

   The agents in the model determine their behaviour, which determines whether they intend to follow the visitors measure or not, on the basis of different needs. Each of these needs seems plausible, as they all appear to exist in the real-life case that is modelled. The HUMAT framework turned out to provide an excellent architecture for constructing these needs in the model, because mapping them onto the needs structure in the framework was very intuitive.

   Moreover, the HUMAT framework was flexible in the sense that certain needs could easily be utilized in a different manner while maintaining the foundations in psychological and sociological theory as the basis of the framework. This flexibility allowed, for example, the implementation of the social needs as a mechanism outside of the evaluation and determination of behaviour, in contrast to the original implementation of social needs in the HUMAT framework.

   Additionally, the implementation of needs was very adaptable, such that it was easy to make extensions to the HUMAT framework. For example, adding the difference between desired and actual hours of contact and the opinion to the evaluations of behaviour was easily implemented.

Given these considerations, we conclude that the HUMAT framework was suitable for modelling the researched case in this thesis.

(b) *To which extent can this model realistically capture the dynamics in this interaction?*

Of course, a model is always an abstraction, meaning it can only be realistic up to a certain extent. Some constraints to the model are that the network is fixed and assumed to consist of individual agents who have to meet in order to fulfil their experiential need to come into contact. Realistically, agents would both live together and have other means of fulfilling their needs. However, implementing all aspects that are realistic to the model would both result in a far too complex model and be too time-consuming. Hence, it is chosen to implement some model aspects as simplifications of real life. Despite these simplifications, the model does show some behaviour that appears to be realistic with respect to the support for the visitors measure and amount of contact that the HUMATs have, which can be useful and insightful.

(c) *Is the data from RIVM surveys[1] sufficient to initialize the HUMATs' opinions with?*

Given the implementation of the model, the opinions will converge to a certain mean over time, depending on the allowed number of visitors. So, in such an end state, the initial opinions are not very relevant. However, the end state of the model is not necessarily the point of interest for the model. If we consider the behaviour of the model during 100 days, the RIVM survey data is relevant and makes a difference in the behaviour of the model. For example, if the HUMAT population is initialized with relatively supportive opinions, but with a strict visitors measure, the model is able to show the transition to a less-supportive population. It can also show the effects of very stubborn individuals, something that can notably be seen in the 3D histogram in Figure 4.11, in the continuation of some opinions as lines. From these perspectives, initializing the HUMATs' opinions with the RIVM survey data is very relevant and can be insightful.

Regardless, it can be said that initializing the opinions of the HUMATs according to a distribution similar to empirical data is valuable in itself.

2. *What can an agent-based model in which the interaction between the support for the Dutch COVID visitors measure and the need for social contact is modelled teach us?*

From running the model we observe some interesting behaviour in terms of the number of contacts and the opinion the HUMATs have during a run, and as the mean of numerous runs. Figure 4.17 shows a divergence between the number of daily contacts

[1] see https://www.rivm.nl/gedragsonderzoek/maatregelen-welbevinden/draagvlak

and mean opinion as the visitors measure becomes stricter. In the answer to the following sub-questions, we will interpret these results and aim to explain why these effects occur for support and efficacy respectively.

(a) *How does the support for the visitors measure change as a result of the strictness of the measure?*

It can be observed in Figures 4.13 and 4.14 that the most lenient visitors measures (8 to 10 allowed visitors per day) result in relatively minor differences in support. In contrast, for stricter visitors measures, the decrease in support is increasingly larger, with the largest differences in support between 1 and 2 allowed visitors.

Relating these results to real life, the displayed differences in support appear plausible, as interacting with 8, 9 or 10 visitors on a day will make a minor difference for the majority of people, while the difference between seeing 1 or 2 is much more drastic. For the majority, high numbers of allowed visitors will most likely not interfere too much with their desires and hence they are likely to accept it when the visitors measure allows them to see one person less. However, as the measure becomes stricter, for more and more people their needs might not be satisfied within the limitations, especially for the difference between 1 or 2 visitors[2]. Therefore the support is increasingly lower for stricter measures.

(b) *How does the amount of social interaction change as a result of the strictness of the visitors measure?*

In Figure 4.15 we find that the bar plot resembles an S-shape, in the sense that the differences in total numbers of contacts are the smallest on the ends of the graph (1 or 2, and 8 to 10 allowed visitors), but the largest in the middle (3 to 7 allowed visitors).

Interpreting these results, it may be that 8 to 10 allowed visitors all lead to similar numbers of total contacts for the aforementioned reason that 8 to 10 visitors is already allows more than what many people desire on a day. When the visitors measure becomes stricter, between 3 and 7 allowed visitors, more and more people will find that their desires may not be met, but that their need to follow the measure will lead to a reduction in their amount of contact. This is where the visitors measure shows the largest effect. However, this effect stagnates as the visitors measure becomes even stricter, with 1 or 2 allowed visitors a day. For many people, this limitation subceeds their desires so much, that they are likely to write off the visitors measure. As a result, it is not the case that they will go over the allowed number of visitors by just a little, but rather they will no longer take the visitors measure into account and simply act in accordance with their desires. Therefore, we see that the visitors measure initially is effective, but that this effect

[2] This difference entails someone could not have a couple over for visit, but could only meet one of the pair, which can be seen as impolite for some people.

stagnates as the visitors measure gets increasingly strict.

## 5.2 Future work

Given the exploratory nature of this research in which a real-life situation is modelled from scratch, many options can be further explored. During the development of the model, we experienced a trade-off between making the agents as complete and realistic as possible on the one hand and keeping the model simple to understand on the other hand. Also, with regards to the allocated time for the research, some behaviour in the model is the result of probabilities, which are chosen by doing an educated guess instead of grounding them in theory. As a result, some potential options were not implemented. This section discusses and suggests some improvements and extensions to the model.

### 5.2.1 Improvements

Currently, while running the model, the variety of opinions decreases over time as they draw to a certain mean, given the allowed number of visitors. It is questionable whether this is realistic, as the survey data in Table 3.1 shows a different pattern, in which opinions change less drastically between survey waves in comparison to the model. Ideally, the model could show the transitions in opinions between these survey waves. Adding *stubbornness* to the HUMATs with regards to their opinions seemed like a plausible addition and it worked effectively as an inhibitor of the opinion-changing effects, which therefore led to a bigger variation of opinions over time. However, stubbornness weights have the downside of being somewhat arbitrary, since they are random floats assigned to the agents. An improvement would be to adjust the stubbornness mechanism to something less arbitrary or to implement a new mechanism that maintains the variety of opinions while being grounded in scientific theory.

Moreover, in their survey, RIVM has also asked the participants about their compliance to follow the measures. An interesting improvement to the model could be to relate the compliance as is shown by the HUMATs in the model to the compliance reported in the survey data.

### 5.2.2 Extensions

For future work, two extensions to the model could be:

- **Dynamic network/connections:** The network of HUMATs is fixed, such that the same connections remain over the course of a run. An interesting extension could be to investigate how the model would behave if some connections could be broken (e.g., if two HUMATs differ sufficiently in their opinion while interacting over time) and other connections could be formed. Adding a dynamic mechanism to the network potentially adds interesting opinion clustering effects to the model.

- **Fear:** Right now, the model includes fear only implicitly, in the sense that a HUMAT's value need to maintain general health is related to a fear that loved ones might get sick from the virus. However, fear could be modelled more explicitly. We observe that during the beginning of the pandemic, *fear of the unknown* initially played a role for people to socially distance themselves from others. Over time, as more knowledge regarding the virus was gained, this fear also decreased. A similar mechanism could be added to the model, such that initially the HUMATs will experience more fear and be more likely to act safely, while over time this fear decreases.

## 5.3 Relevance

Firstly, since the use of theoretically grounded agent-based models is a relatively new development within the social sciences, this research contributes to the idea of integrating a cognitive framework in an ABM. In general, using a psychologically founded framework as the basis for the agents' decision-making improves the probability that the simulation captures some phenomena that can be observed in reality. Moreover, it facilitates an architecture that leads to intuitive choices during the development of a model and offers the possibility to compare different implementations of the framework, while maintaining the same base structure. The HUMAT framework turned out to be very suitable for this case since it was easy to map the agents' needs to the architecture. Given the fact that these needs are intuitively plausible, using the HUMAT framework led to a model that is understandable not only to people who understand the code but also to social scientists in general and laymen. Consequently, this work has shown the potential of applying the HUMAT framework to ABM and can be applied to many other cases.

Secondly, regarding the specific topic of this thesis, namely, social interaction in times of COVID restrictions. For many, this is the first time they experience a pandemic at this scale. Unfortunately, with the current manner in which we manage livestock, we are creating an environment in which the probability of another zoonosis is very high. Consequently, the rate of pandemics at this scale is increasing. Given these predictions, it is not a matter of *if*, but *when* the next pandemic will be. With a model based on historical data on epidemic frequency and geographic distribution, researchers predict there is a 47-57 percent chance of another global pandemic as deadly as COVID in the next 25 years (Smitham & Glassman, August 2021). At the time the next pandemic will take place, we hope this work may contribute to finding the optimal policy with regards to visitor-restricting measures, such that both physical and mental health are maintained.

## 5.4 Conclusion

In this thesis, the development of a novel agent-based model was described that aims to explore social interaction while it is constrained by visitor limitations. Specifically, this thesis aimed to capture the interaction between the need for social contact and the support for the visitors measure. The model was developed using the HUMAT integrated framework, which offered a psychological and sociological foundation for the behaviour of the agents.

Considering the results throughout Chapter 4 and the answers to the research questions in Section 5.1, we observe that the model shows a trade-off between efficacy and support for the visitors measure. Initially, making the policy stricter will be effective in reducing the amount of contact between HUMATs, while lowering the support for the policy relatively little. However, at a certain policy strictness, the effects to the amount of contact stagnate, while the support for the policy continues to decrease.

Given the insights from this work, a sweet spot could exist in terms of the strictness of the policy, in which the visitors measure is relatively effective, while the population remains sufficiently satisfied. The current policy seems to be mostly aimed at reducing the amount of contact at all costs. However, considering the overall happiness of the population may have its benefits on reducing mental health issues.

## Model documentation

The model presented in this thesis was implemented in NetLogo 6.2. The model (source code and interface) can be found at `https://github.com/boscy/SimulatingSocialInteraction`. The experimental setups can be found in BehaviorSpace of the NetLogo model and the data gained from the experiments in the *experimental_data* folder. The repository also includes a folder containing the R-scripts used for analyzing experimental data and a csv file of the RIVM survey data on the support for the visitors measure, which can be used for the initialization of the agents' opinions.

# References


Antosz, P., Jager, W., Polhill, G., Salt, D., Scalco, A., Alonso-Betanzos, A., ... Rodríguez, A. (2019). D7.2-Simulation model implementing different relevant layers of social innovation, human choice behaviour and habitual structures. Report describing the theoretical principles of the model and justification and clarification of assumptions used. *Technical report, European Union Horizon 2020 research and innovation programme under grant agreement No. 763912.*.

Augustine, A. A., & Hemenover, S. H. (2012). Extraversion, social interaction, and affect repair. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning* (pp. 1253–1255). Boston, MA: Springer US. Retrieved from https://doi.org/10.1007/978-1-4419-1428-6_1744 doi: 10.1007/978-1-4419-1428-6_1744

Backer, J. A., Mollema, L., Klinkenberg, D., van der Klis, F., Melker, H. d., van den Hof, S., & Wallinga, J. (2020). The Impact of Physical Distancing Measures Against COVID-19 Transmission on Contacts and Mixing Patterns in the Netherlands: Repeated Cross-Sectional Surveys. *medRxiv*. Retrieved from https://www.medrxiv.org/content/early/2020/05/20/2020.05.18.20101501 doi: 10.1101/2020.05.18.20101501

Bascompte, J., & Sole, R. (1996). Habitat Fragmentation and Extinction Thresholds in Spatially Explicit Models. *The Journal of Animal Ecology*, *65*, 465-473.

Bellifemine, F. L., Caire, G., & Greenwood, D. (2007). *Developing Multi-Agent Systems with JADE (Wiley Series in Agent Technology)*. Hoboken, NJ, USA: John Wiley Sons, Inc.

Campbell, D. T. (1974). Downward Causation. In F. Ayala & T. Dobzhansky (Eds.), *Studies in the Philosophy of Biology* (pp. 179–186). University of California Press.

CANS. (January 2022). *Meer suïcides onder jongvolwassenen tussen 20 en 30 jaar.* https://www.113.nl/actueel/meer-suicides-onder-jongvolwassenen-tussen-20-en-30-jaar. (Accessed: 2022-01-17)

Cialdini, R. B., & Goldstein, N. J. (2004). Social Influence: Compliance and Conformity. , *55*(1), 591–621. Retrieved 2013-02-17, from http://www.annualreviews.org/doi/abs/10.1146/annurev.psych.55.090902.142015 doi: 10.1146/annurev.psych.55.090902.142015

Epstein, J. (1999). Agent-based Computational Models and Generative Social Science. *Complexity*, *4*(5), 41-60. doi: https://doi.org/10.1002/(SICI)1099-0526(199905/06)4:5<41::AID-CPLX9>3.0.CO;2-F

Epstein, J. (2006). *Generative Social Science: Studies in Agent-Based Computational Models*. Princeton University Press.

Ernst, A. M. (1998). Resource Dilemmas, Computer Simulated Actors and Climate Change - a Methodology to Investigate Human Behavior in a Complex Domain. In E. A. Stuhler & D. J. DeTombe (Eds.), *Complex Problem Solving - Cognitive Psychological Issues and Environmental Policy Applications.* Hampp press; 1998.

Flache, A., Mäs, M., Feliciani, T., Chattoe-Brown, E., Deffuant, G., Huet, S., & Lorenz, J. (2017). Models of Social Influence: Towards the Next Frontiers. *Journal of Artificial Societies and Social Simulation*, *20*(4), 2. Retrieved from http://jasss.soc.surrey.ac.uk/20/4/2.html doi: 10.18564/jasss.3521

Ghaffarzadegan, N. (2021). Simulation-based what-if analysis for controlling the spread of covid-19 in universities. *PLOS ONE*, *16*(2), 1-24. Retrieved from https://doi.org/10.1371/journal.pone.0246323 doi: 10.1371/journal.pone.0246323

Gigerenzer, G., Todd, P., & Group, A. (1999). *Simple Heuristics that Make us Smart*. Great Clarendon St, Oxford OX2 6DP, United Kingdom: Oxford University Press.

Gilbert, N. (1995). *Emergence in Social Simulation*. London: UCL press.

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the Social Scientist*. Maidenhead, Berkshire, United Kingdom: Open University Press; 2nd edition.

Gloster, A. T., Lamnisos, D., Lubenko, J., Presti, G., Squatrito, V., Constantinou, M., ... Karekla, M. (2021). Impact of COVID-19 pandemic on mental health: An international study. *PLOS ONE*, *15*(12), 1-20. Retrieved from https://doi.org/10.1371/journal.pone.0244809 doi: 10.1371/journal.pone.0244809

Grow, A., Flache, A., & Wittek, R. P. M. (2017). Global Diversity and Local Consensus in Status Beliefs: The Role of Network Clustering and Resistance to Belief Change. *Sociological Science*, *4*(25), 611–640. Retrieved from http://dx.doi.org/10.15195/v4.a25 doi: 10.15195/v4.a25

Harvey, N., Reeves, A., Schoenbaum, M. A., Zagmutt-Vergara, F. J., Dubé, C., Hill, A. E., ... Salman, M. D. (2007). The North American Animal Disease Spread Model: a Simulation Model to Assist Decision Making in Evaluating Animal Disease Incursions. *Preventive Veterinary Medicine*, *82*(3-4), 176—197. Retrieved from https://doi.org/10.1016/j.prevetmed.2007.05.019 doi: 10.1016/j.prevetmed.2007.05.019

Hemelrijk, C., & Hildenbrandt, H. (2008). Self-organized shape and frontal density of fish schools. *Ethology*, *114*(3), 245–254. (ISI:000253145700006) doi: 10.1111/j.1439-0310.2007.01459.x

Heylighen, F. (2011). Self-organization of Complex, Intelligent Systems: an Action Ontology for Transdisciplinary Integration. Integral Review (in press).

Howorth, G. (2020). *How to Differentiate Between Multi-Agent Systems and Agent-Based Models?* https://www.researchgate.net/post/How_to_differentiate_between_multi-agent_systems_and_agent-based_models. (Accessed: 2021-09-10)

Jager, W. (2000). *Modelling consumer behaviour.* (Thesis Behavioural and Social Sciences, University of Groningen. https://www.rug.nl/research/portal/files/9914467/thesis.pdf)

Jager, W. (2021). Using Agent Based Modelling to Explore Behavioural Dynamics Affecting our Climate. *Current Opinion in Psychology*, *42*, 133-139. Retrieved from https://www.sciencedirect.com/science/article/pii/S2352250X21000968 doi: https://doi.org/10.1016/j.copsyc.2021.06.024

Johnson, C. R., & Seinen, I. (2002). Selection for Restraint in Competitive Ability in Spatial Competition Systems. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, *269*(1492), 655-663. Retrieved from https://royalsocietypublishing.org/doi/abs/10.1098/rspb.2001.1948 doi: 10.1098/rspb.2001.1948

Kallgren, C. A., Reno, R. R., & Cialdini, R. B. (2000). A Focus Theory of Normative Conduct: When Norms Do and Do not Affect Behavior. *Personality and Social Psychology Bulletin*, *26*(8), 1002-1012. Retrieved from https://doi.org/10.1177/01461672002610009 doi: 10.1177/01461672002610009

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An Agent-based Model for Diffusion of Electric Vehicles. *Journal of Environmental Psychology*, *52*, 166–182. doi: 10.1016/j.jenvp.2017.01.002

Kubo, T., Iwasa, Y., & Furumoto, N. (1996). Forest Spatial Dynamics with Gap Expansion: Total Gap Area and Gap Size Distribution. *Journal of Theoretical Biology*, *180*(3), 229-246. Retrieved from https://www.sciencedirect.com/science/article/pii/S0022519396900995 doi: https://doi.org/10.1006/jtbi.1996.0099

Latané, B. (1996). Dynamic Social Impact: The Creation of Culture by Communication. *Journal of Communication*, *46*, 13-25.

Lifelines. (February 2021). *Mentale Gezondheid Daalt tot Dieptepunt sinds begin Coronacrisis.* https://www.rug.nl/news/2021/02/mentale-gezondheid-daalt-tot-dieptepunt-sinds-begin-coronacrisis. (Accessed: 2021-03-25)

Mc Intyre, K., Lanting, P., Deelen, P., Wiersma, H. H., Vonk, J. M., Ori, A. P. S., ... Franke, L. (2021). Lifelines COVID-19 cohort: investigating COVID-19 infection and its health and societal impacts in a Dutch population-based cohort. *BMJ Open*, *11*(3). Retrieved from https://bmjopen.bmj.com/content/11/3/e044474 doi: 10.1136/bmjopen-2020-044474

Newell, B. R., Lagnado, D. A., & Shanks, D. R. (2007). *Straight Choices: The Psychology of Decision Making* . Psychology Press Hove, England.

Niazi, M., & Hussain, A. (2011). Agent-based Computing from Multi-agent Systems to Agent-based Models: a Visual Survey. *Scientometrics*, *89*, 479-499. doi: 10.1007/s11192-011-0468-9

Nishimura, S. I. (2002). A Predator's Selection of an Individual Prey from a Group. *Bio Systems*, *65*(1), 25—35. Retrieved from https://doi.org/10.1016/s0303-2647(01)00191-5 doi: 10.1016/s0303-2647(01)00191-5

Olberg, R., Worthington, A., & Venator, K. R. (2000). Prey Pursuit and Interception in Dragonflies. *Journal of Comparative Physiology A*, *186*, 155-162.

Parrish, J. K. (1993). Comparison of the Hunting Behavior of Four Piscine Predators Attacking Schooling Prey. *Ethology*, *95*(3), 233-246. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1439-0310.1993.tb00473.x doi: https://doi.org/10.1111/j.1439-0310.1993.tb00473.x

Prandi, L., & Primiero, G. (2020). Effects of Misinformation Diffusion during a Pandemic. *Applied Network Science*, *5*. doi: 10.1007/s41109-020-00327-6

Sample, I. (December 2020). *Covid poses 'greatest threat to mental health since second world war'.* https://www.theguardian.com/society/2020/dec/27/covid-poses-greatest-threat-to-mental-health-since-second-world-war. (Accessed: 2021-03-25)

Schelling, T. C. (1971). Dynamic models of segregation. *The Journal of Mathematical Sociology*, *1*(2), 143-186. Retrieved from https://doi.org/10.1080/0022250X.1971.9989794 doi: 10.1080/0022250X.1971.9989794

Schelling, T. C. (1974). On the Ecology of Micromotives. In R. Marris (Ed.), *The Corporate Society* (pp. 19–64). London: Macmillan Education UK. Retrieved from https://doi.org/10.1007/978-1-349-01977-9_2 doi: 10.1007/978-1-349-01977-9_2

Sherif, M., & Hovland, C. (1961). *Social Judgment: Assimilation and Contrast Effects in Communication and Attitude Change*. Yale University Press, New Haven, CT.

Shoham, Y. (1993). Agent-Oriented Programming. *Artificial Intelligence*, *60*(1), 51-92. Retrieved from https://www.sciencedirect.com/science/article/pii/0004370293900349 doi: https://doi.org/10.1016/0004-3702(93)90034-9

Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, *69*(1), 99–118. Retrieved from http://www.jstor.org/stable/1884852

Simon, H. A. (1956). Rational Choice and the Structure of the Environment. *Psychological Review*, *63 2*, 129-38.

Smitham, E., & Glassman, A. (August 2021). *The Next Pandemic Could Come Soon and Be Deadlier.* https://www.cgdev.org/blog/the-next-pandemic-could-come-soon-and-be-deadlier. (Accessed: 2022-02-04)

Szabó, G., & Czárán, T. (2001). Defensive Alliances in Spatial Models of Cyclical Population Interactions. *Phys. Rev. E*, *64*, 042902. Retrieved from https://link.aps.org/doi/10.1103/PhysRevE.64.042902 doi: 10.1103/PhysRevE.64.042902

Tunstrom, K., Katz, Y., Ioannou, C., Huepe, C., Lutz, M., & Couzin, I. (2013). Collective States, Multistability and Transitional Behavior in Schooling Fish. *PLoS Computational Biology*, *9*(2). doi: 10.1371/journal.pcbi.1002915

Varian, H. R. (1992). *Microeconomic Analysis* (Third ed.). New York: Norton.

Wooldridge, M. (2009). *An Introduction to MultiAgent Systems* (2nd ed.). Wiley Publishing.

Wooldridge, M., & Jennings, N. R. (1995). Intelligent Agents: Theory and Practice. *The Knowledge Engineering Review*, *10*(2), 115–152. doi: 10.1017/S0269888900008122

Zheng, M., Kashimori, Y., Hoshino, O., Fujita, K., & Kambara, T. (2005). Behavior Pattern (Innate Action) of Individuals in Fish Schools Generating Efficient Collective Evasion from Predation. *Journal of Theoretical Biology*, *235*(2), 153—167. Retrieved from https://doi.org/10.1016/j.jtbi.2004.12.025 doi: 10.1016/j.jtbi.2004.12.025

# Appendices

# A | MODEL SCREENSHOTS

This chapter provides various screenshots of the NetLogo model interface.

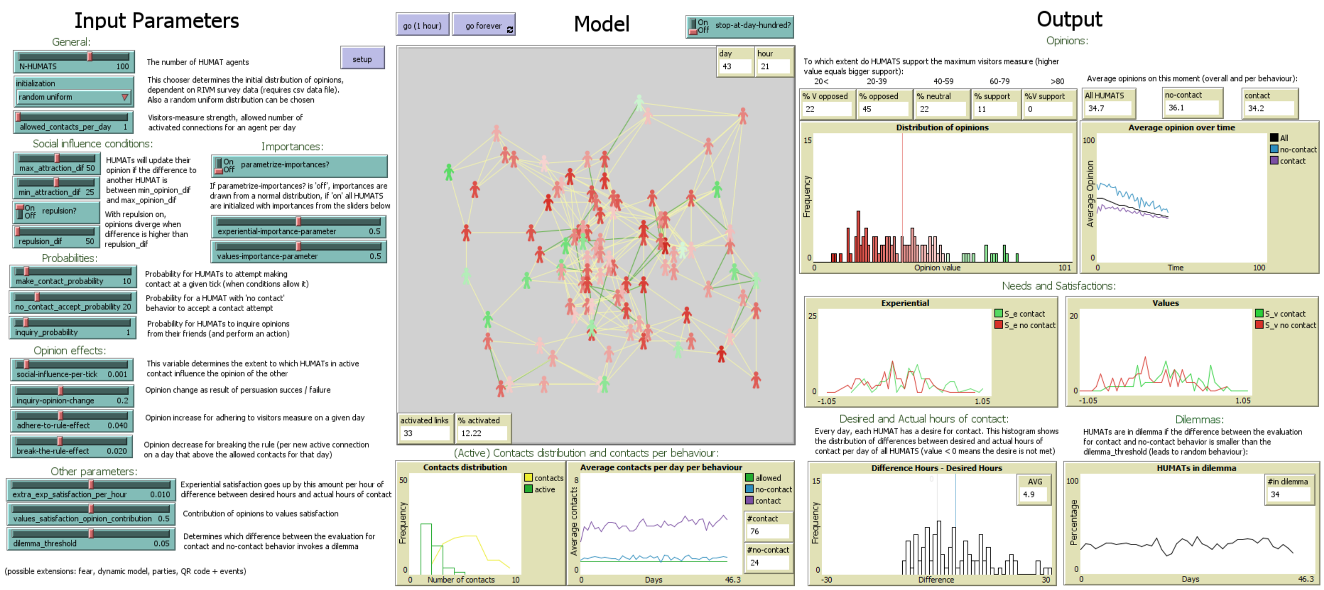


Figure A.1: Screenshot of the full model's NetLogo interface.

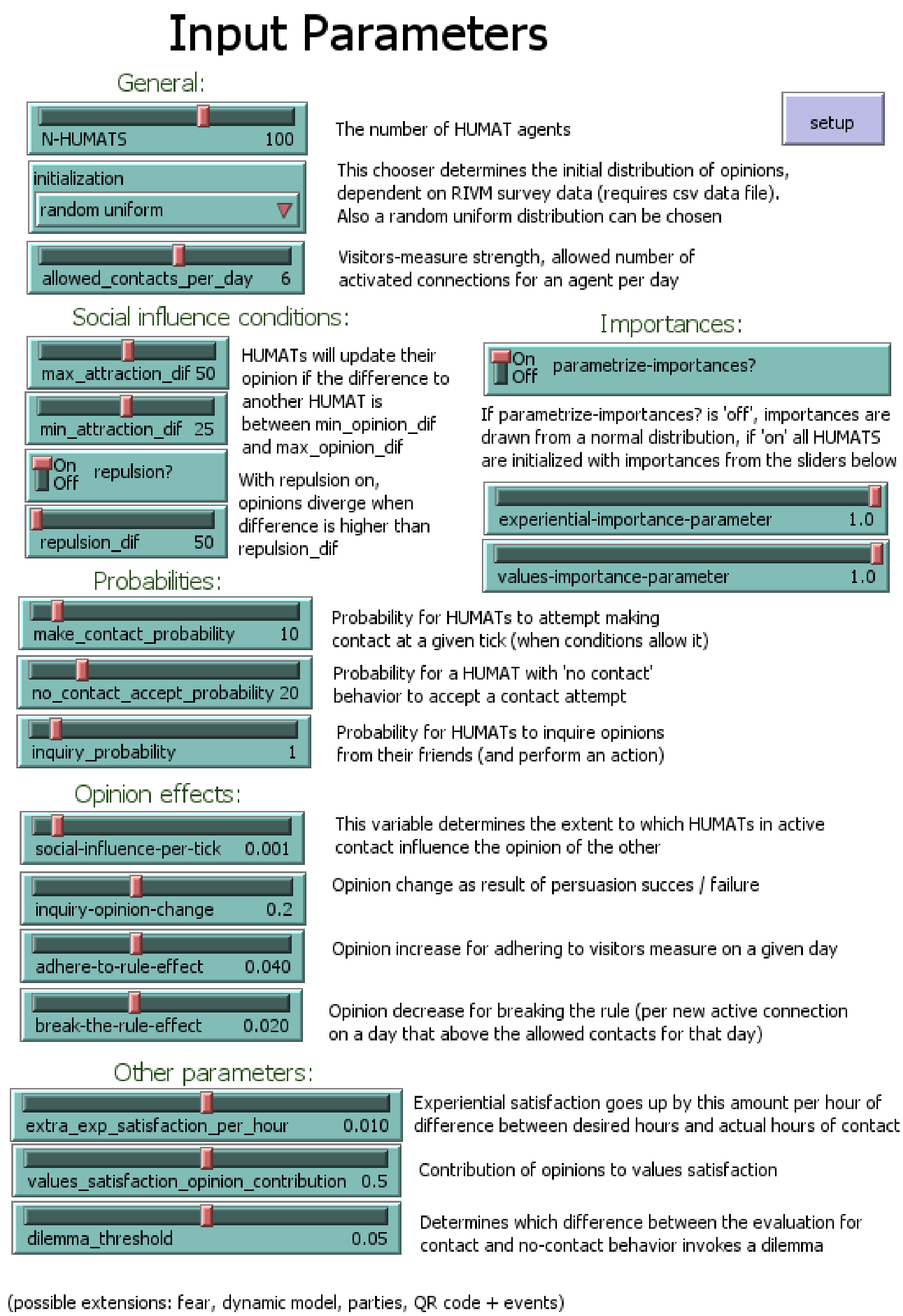



Figure A.2: *Input parameters* section of the model's NetLogo interface.

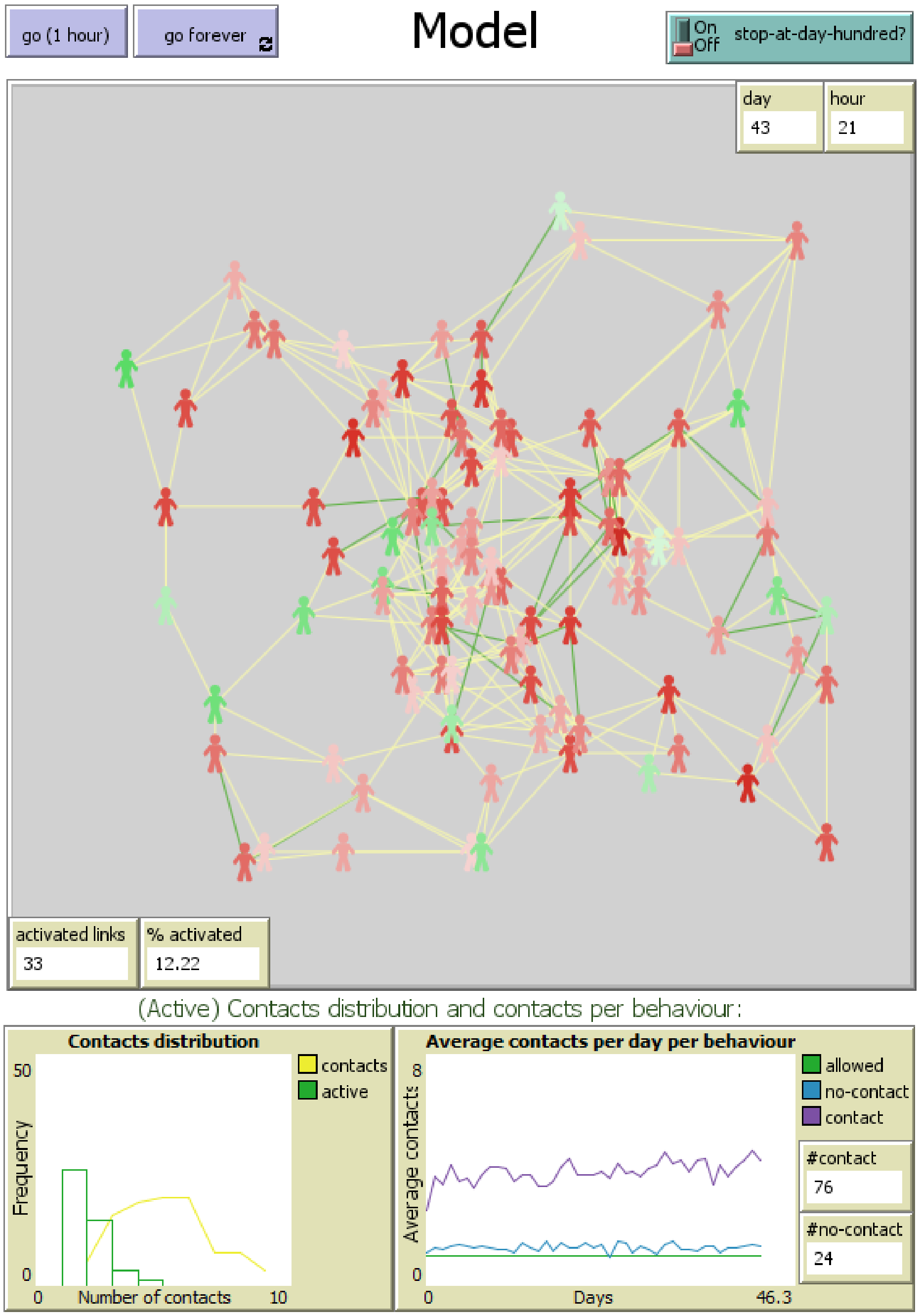



Figure A.3: *Model* section of the model's NetLogo interface.

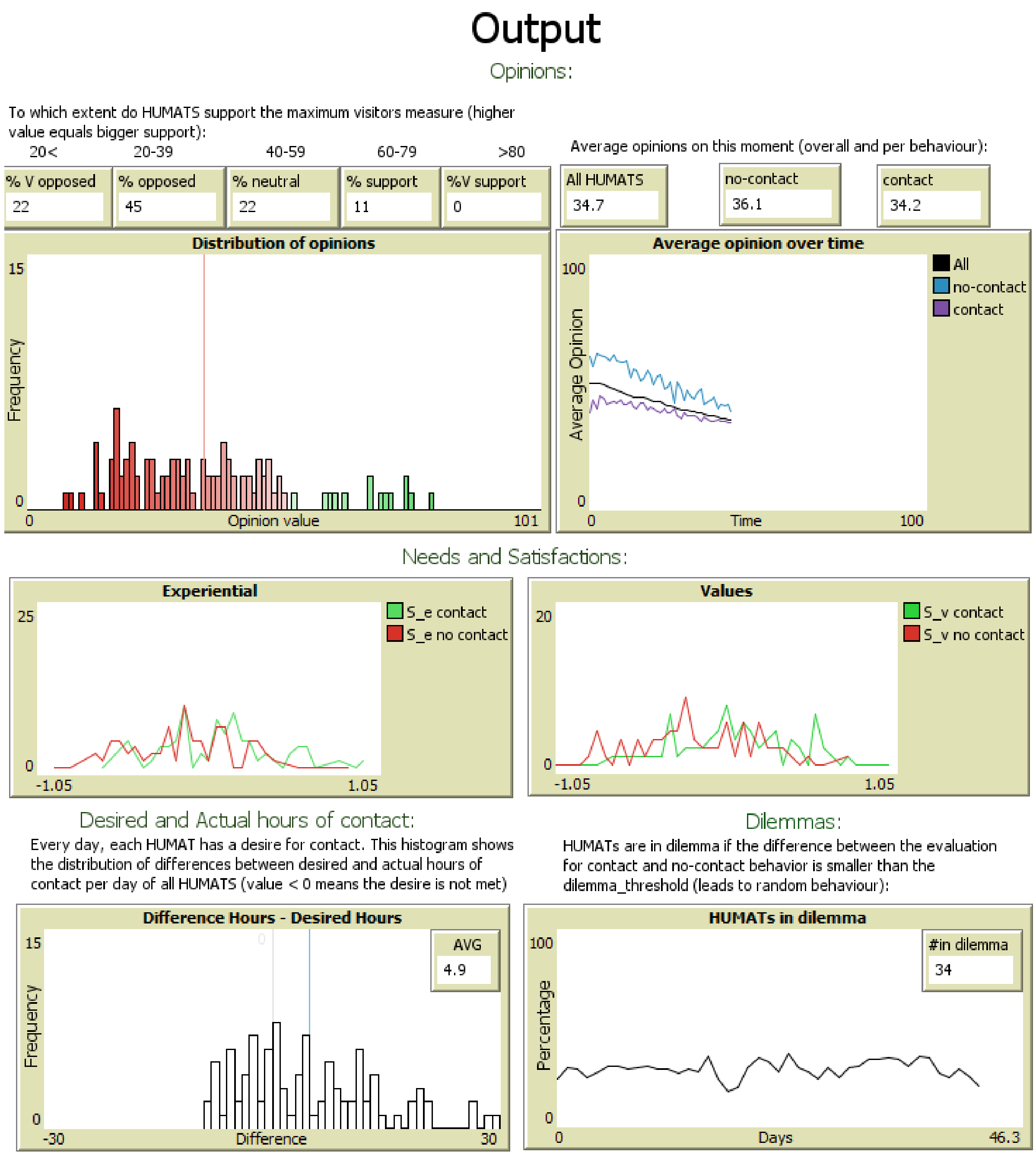



Figure A.4: *Output* section of the model's NetLogo interface.

# B | RESULTS OF HUMAT IMPORTANCES PARAMETER SWEEP

This appendix shows the results for the experiment described in Section 4.3

## B.1 Mean values

The first set of results concerns the *mean values* during the runs. The following metrics are considered:

- The average number of active contacts per HUMAT during the runs,
- The average number of HUMATs that are in a dilemma during the runs,
- The mean opinion during the runs, and
- The standard deviation of the opinion during the runs.

### B.1.1 2 allowed visitors per day

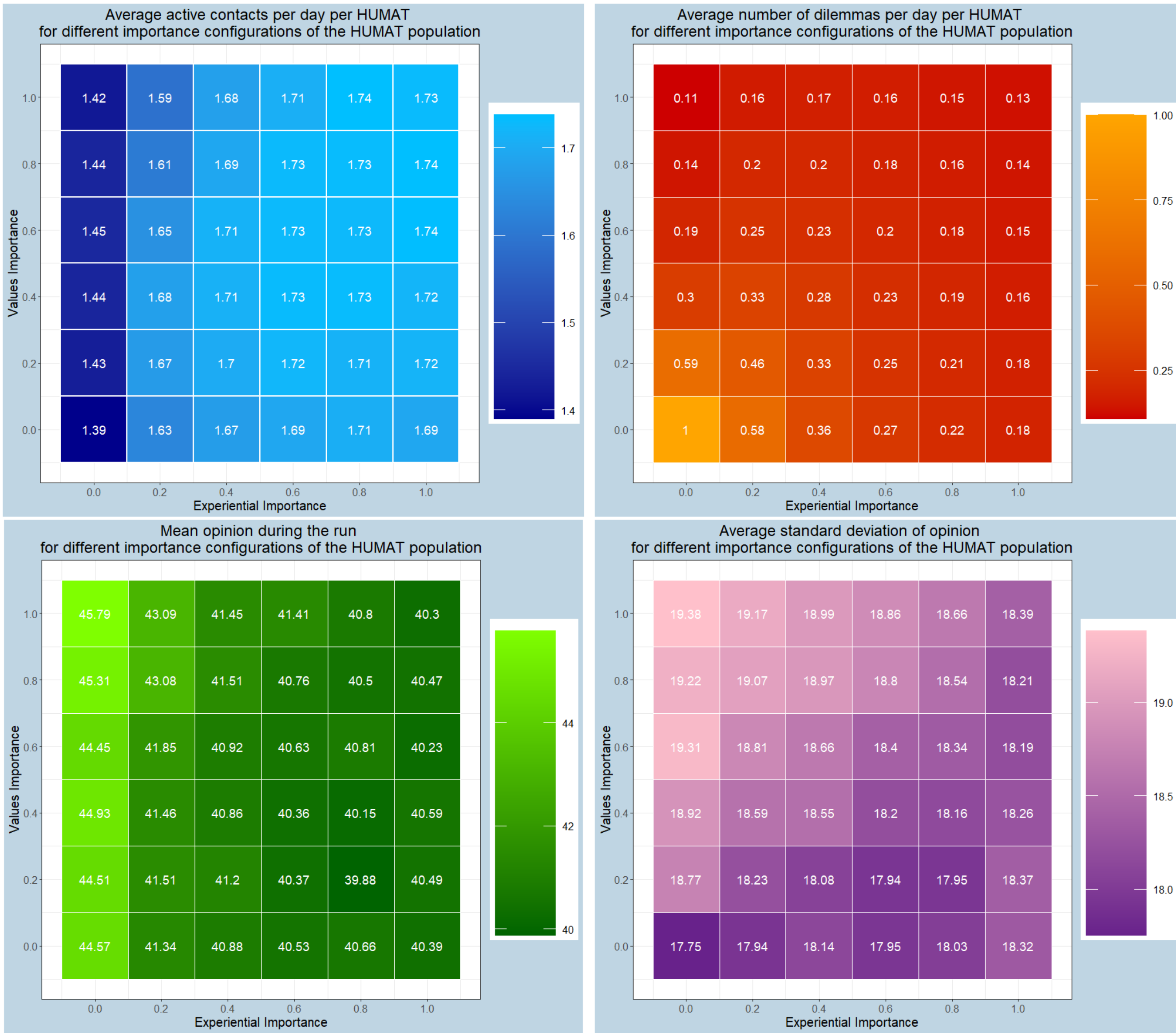



Figure B.1: Importance parameters sweep results for 2 allowed visitors per day: *Mean values*: Upper left (blue): the average number of active contacts per day per HUMAT. Upper right (red): the average number of dilemmas per day per HUMAT. Bottom left (green): the mean opinion of the HUMAT population during the runs. Bottom right (purple): the average standard deviation of the opinion during the runs.

### B.1.2 4 allowed visitors per day:

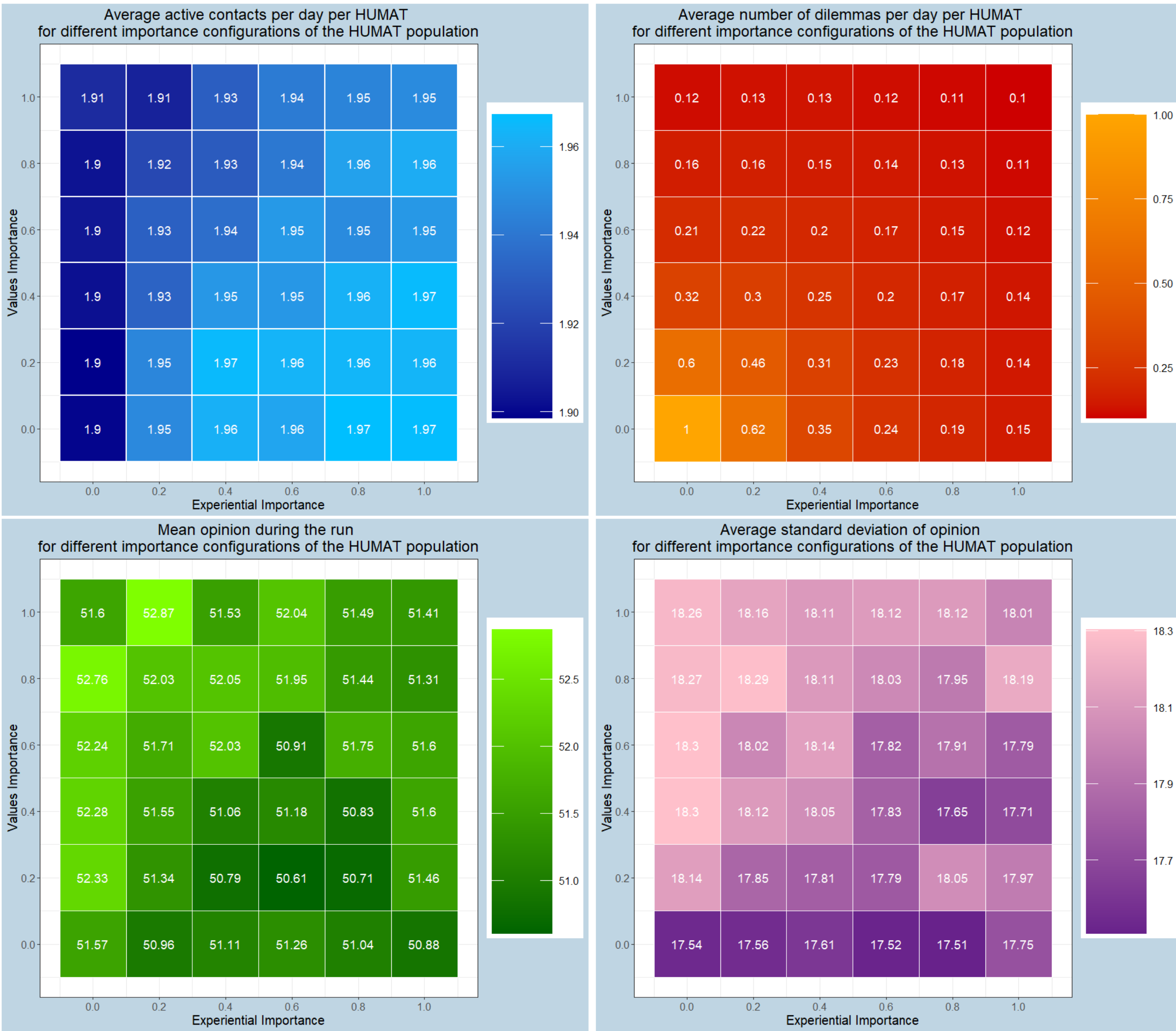



Figure B.2: Importance parameters sweep results for 4 allowed visitors per day: *Mean values*: Upper left (blue): the average number of active contacts per day per HUMAT. Upper right (red): the average number of dilemmas per day per HUMAT. Bottom left (green): the mean opinion of the HUMAT population during the runs. Bottom right (purple): the average standard deviation of the opinion during the runs.

### B.1.3 6 allowed visitors per day:

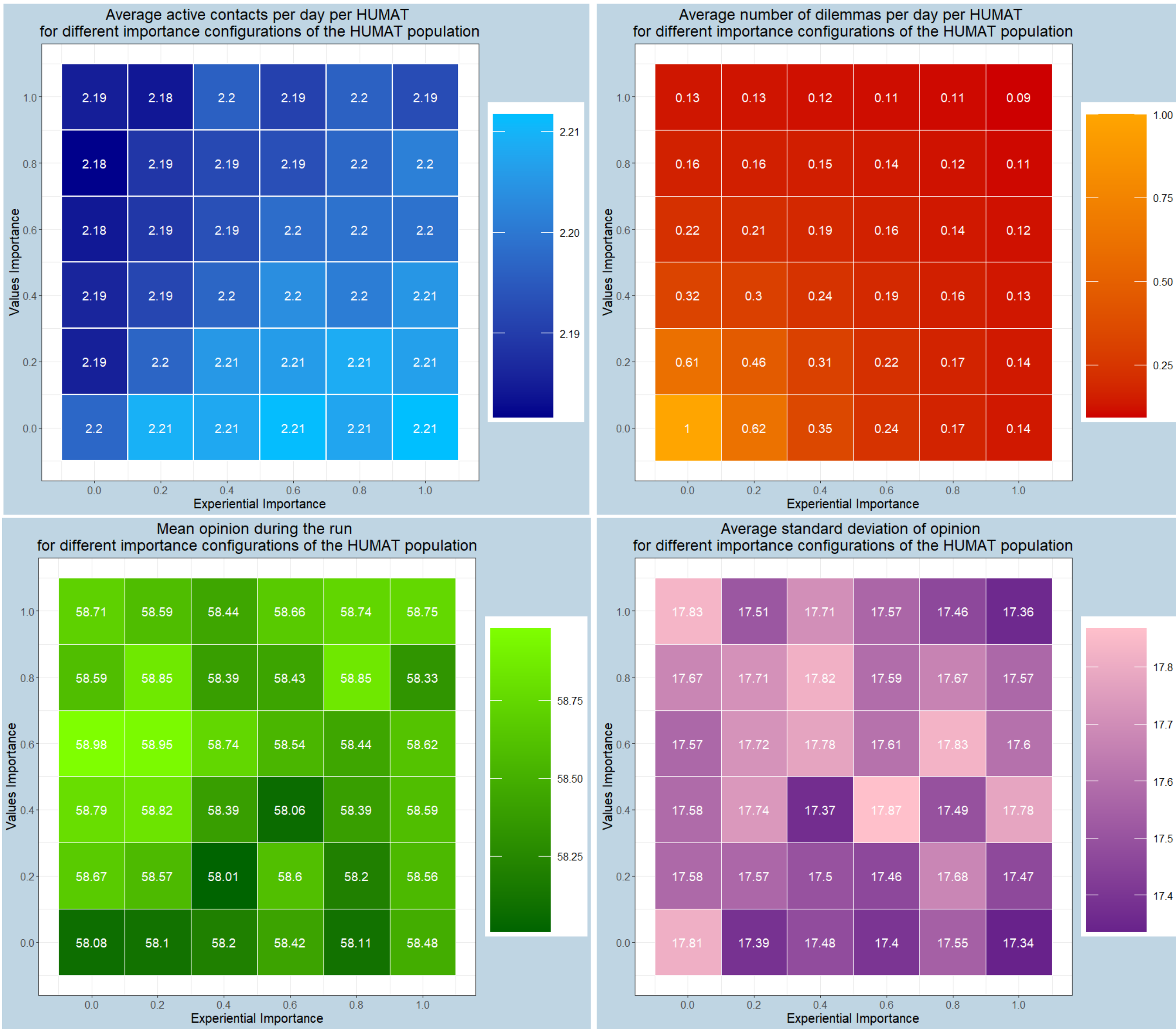



Figure B.3: Importance parameters sweep results for 6 allowed visitors per day: *Mean values*:
Upper left (blue): the average number of active contacts per day per HUMAT. Upper right (red): the average number of dilemmas per day per HUMAT. Bottom left (green): the mean opinion of the HUMAT population during the runs. Bottom right (purple): the average standard deviation of the opinion during the runs.

## B.2 Final-day values

The second set of results concerns the *final-day values* during the runs. The following metrics are considered:

- The average number of active contacts per HUMAT on the final day of the runs,
- The average number of HUMATs that are in a dilemma on the final day of the runs,
- The mean opinion on the final day of the runs, and
- The standard deviation of the opinion on the final day of the runs.

### B.2.1 2 allowed visitors per day

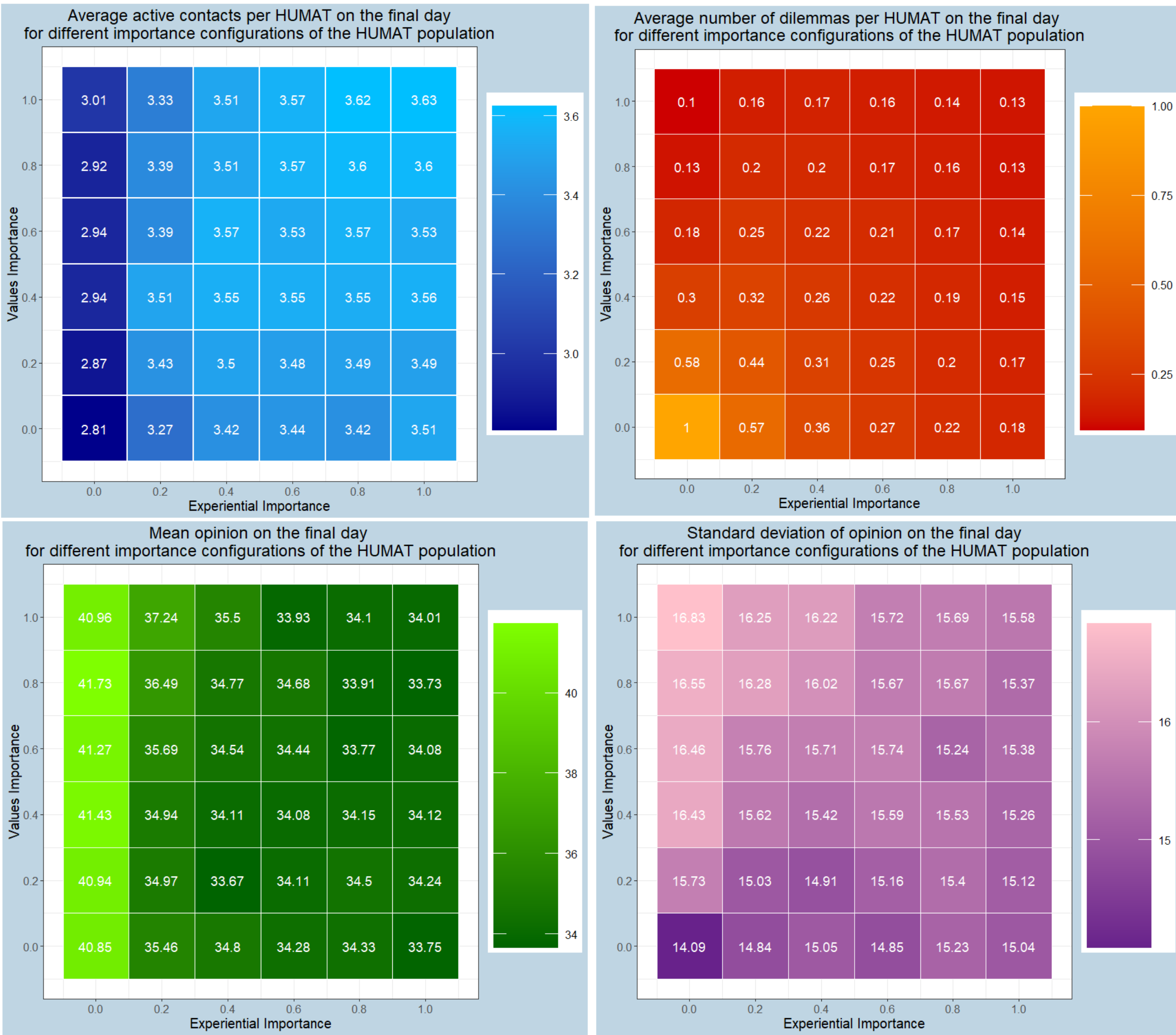



Figure B.4: Importance parameters sweep results for 2 allowed visitors per day: *Final values*: Upper left (blue): the average number of active contacts on the final day per HUMAT. Upper right (red): the average number of dilemmas on the final day per HUMAT. Bottom left (green): the mean opinion of the HUMAT population on the final day. Bottom right (purple): the average standard deviation of the opinion on the final day.

### B.2.2 4 allowed visitors per day:

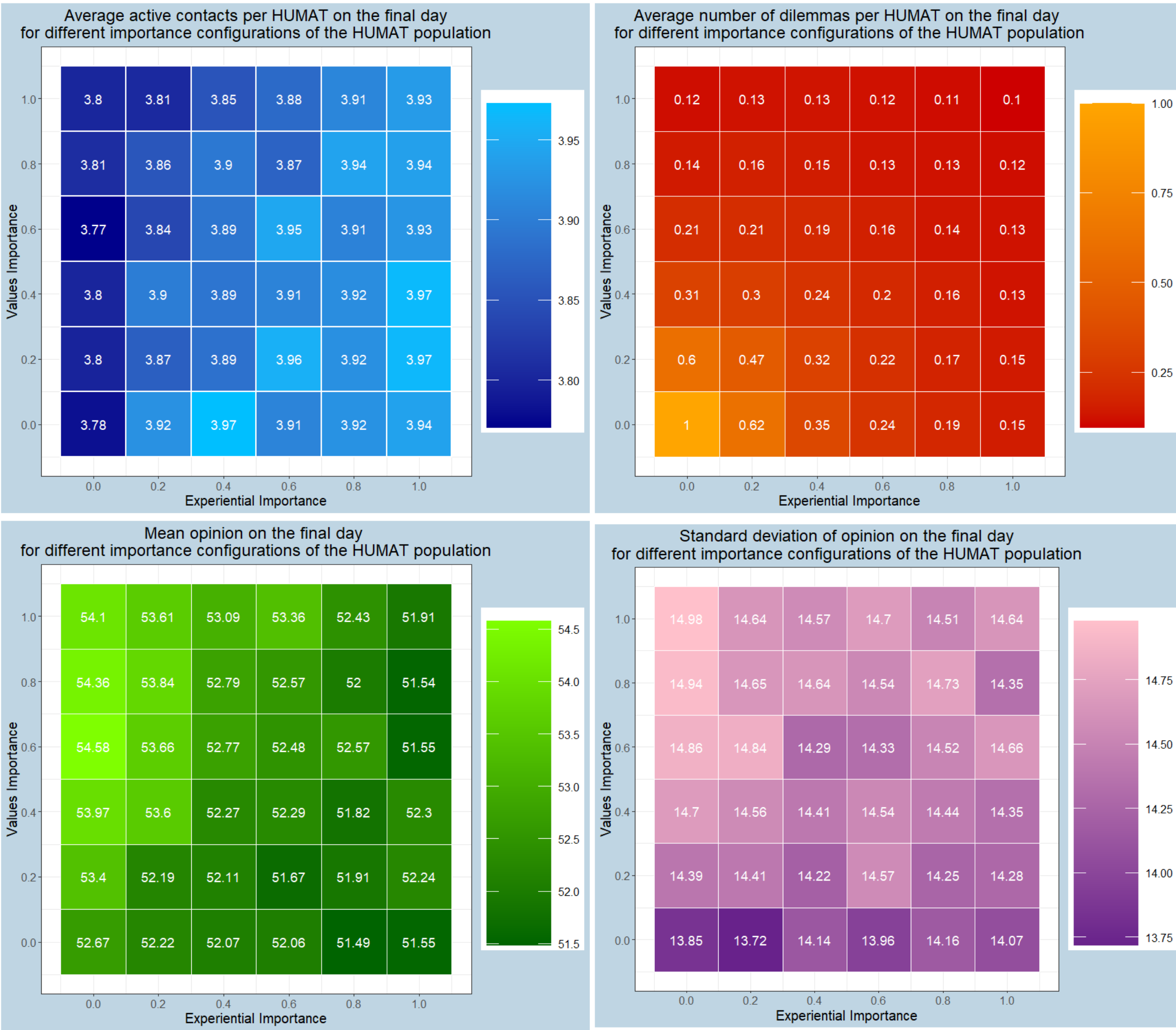



Figure B.5: Importance parameters sweep results for 4 allowed visitors per day: *Final values*: Upper left (blue): the average number of active contacts on the final day per HUMAT. Upper right (red): the average number of dilemmas on the final day per HUMAT. Bottom left (green): the mean opinion of the HUMAT population on the final day. Bottom right (purple): the average standard deviation of the opinion on the final day.

### B.2.3 6 allowed visitors per day:

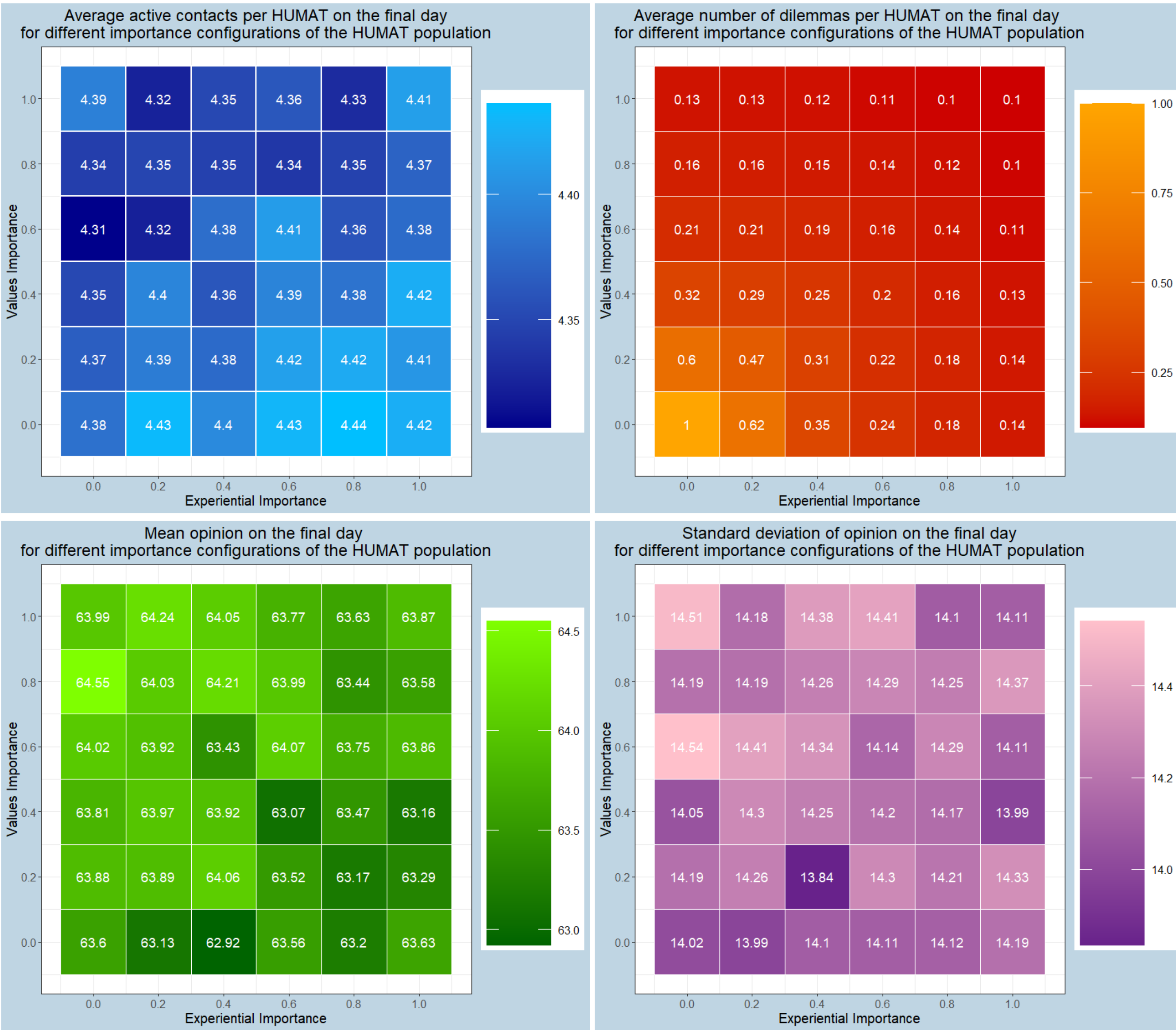



Figure B.6: Importance parameters sweep results for 6 allowed visitors per day: *Final values*:
Upper left (blue): the average number of active contacts on the final day per HUMAT. Upper right (red): the average number of dilemmas on the final day per HUMAT. Bottom left (green): the mean opinion of the HUMAT population on the final day. Bottom right (purple): the average standard deviation of the opinion on the final day.