Understanding the Free-Rider Problem in COVID-19 Guideline Compliance: A Multi-Agent-Based Approach with Theory of Mind

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Abstract

Theory of Mind has been extensively studied in competitive gaming environments, but its role in cooperative scenarios remains less explored. In this paper, we investigate how artificial agents apply Theory of Mind in a cooperative setting, where they face the dilemma of either contributing to a common goal or free-riding to gain a local, individual reward. We expand our research focus on a pandemic scenario where agents have the choice of complying with the guidelines and the common goal of keeping the infection curve at flat levels. Since emerging, the COVID-19 pandemic has not only driven humanity to significant technological advancements but has also triggered new interest in socio-psychological behavior. Numerous studies have modeled infection spread and examined the impact of guidelines and vaccination. In our multi-agent system simulation, we focus on how artificial agents choose to comply or free-ride, if they possess the ability to strategize with Theory of Mind, while also adjusting other parameters that can affect their penalties and rewards.

1 Introduction

Theory of Mind (ToM), or the ability to attribute mental states to others, has been traditionally explored in competitive scenarios, while recent studies have begun to investigate its role in cooperative ones. It is an acknowledgement that ToM is not only important for predicting competitive moves but also for fostering cooperation with enabling individuals to align actions with shared goals. The global pandemic of Covid-19 has impacted global health, economies and people worldwide. Measures such as mask-wearing, social distancing, and lockdown, other than being vital to mitigate the virus' spread, have been a recurrent thought for most. Compliance with these guidelines varies significantly among individuals and communities. Conspiratorial thinking and pandemic fatigue are some of the factors contributing most to the non-compliance [YC21b]. Non-compliant people benefit from the public good without bearing the cost of contributing to it. This behavior is also known as the free-rider problem. Understanding how ToM affects compliance decisions in a pandemic context is crucial. Our research investigates whether individuals with higher ToM are more likely to adhere to public health guidelines, considering the societal impact of their actions. By simulating these dynamics in a multi-agent environment, we aim to determine if advanced ToM capabilities lead to greater compliance, thereby enhancing collective efforts to control infection spread.

1.1 Problem

An individual's interest in short-term gains can lead, in the long run, to a loss for the entire group. Our study focuses on understanding how an individual's capacity of ToM influences their decision to comply with health guidelines.
In the context of COVID-19, where public health guidelines are designed to protect the community, ToM provides a framework for understanding how individuals' social reasoning might influence compliance decisions. Specifically, we aim to explore whether agents with higher ToM are more likely to comply with guidelines because they are aware of the societal consequences of their actions. Therefore, our research question is: How does Theory of Mind impact compliance rates with public health guidelines in a simulated pandemic environment?
The COVID-19 scenario offers insight into how people react to strict guidelines while supporting a common goal. Studying how people react to behavior of others and how this affects their compliance is vital to understanding how to address non-compliance in a cooperative environment. We analyze how individuals with different ToM levels respond to both strict and lenient guidelines, and how observing others' behaviors influences their decisions. By simulating these dynamics in a multi-agent environment, we aim to clarify whether higher levels of ToM contribute to greater compliance through social awareness. This approach is innovative because it models compliance behavior using degrees of ToM, rather than focusing solely on infection transmission.

1.2 Current Research

In order to study in depth the train of thought of the agents, multiple degrees of ToM are applied. The use of ToM in a multi-agent cooperative setting has been extensively studied, and its effectiveness has been proven. ToM agents have been shown to perform superiorly to non-ToM agents, with this improvement greatly increasing upon collaboration with other ToM agents [Cro+24]. Furthermore, the study of [LTO20] demonstrates that ToM agents achieve greater performance and exhibit more "human-like" behavior compared to agents without ToM. This human-like behavior is essential in understanding compliance in realistic scenarios.
Research from the Gläscher Lab [Lab20] demonstrates that ToM significantly impacts both cooperative and competitive contexts by allowing individuals to build mental models of others' intentions, which is essential for cooperation in dynamic social settings. Furthermore, studies reveal that in multi-agent systems, ToM-equipped agents can achieve higher levels of cooperation compared to non-ToM agents, indicating that ToM enhances collaborative dynamics and adherence to group norms. Zhao et al. (2023) propose a brain-inspired model that facilitates cooperation by simulating collective mental states, which proved effective in maintaining cooperation among agents [Zha+23].
Yong and Choy (2021) argue that during the COVID-19 pandemic, compliance and non-compliance with safety guidelines reflected a public goods dilemma, where individual actions directly affected community welfare [YC21a]. In the context of pandemic compliance, the study of ToM in cooperative scenarios is valuable for understanding compliance decisions. By examining agents with varying levels of ToM, we aim to identify whether advanced ToM capabilities result in greater compliance rates, thereby contributing to the collective goal of infection control.
We acknowledge that there is plenty of research attempting to model infection transmission, the impact of regulations, and the impact of COVID-19 on plenty of scenarios. Nevertheless, the virus still has unknown aspects and is hard to model. An attempt to model the COVID-19 pandemic as a public goods dilemma in which public health measures such as mask-wearing and social distancing are collective actions is presented in [YC21b]. The authors identify free-riding behaviour during episodes of noncompliance during the pandemic, studying the causes and outcomes. The study specifically identifies factors, such as conspiratorial thinking and pandemic fatigue, that contribute to noncompliance.

Acknowledging the epidemic as a free-rider problem, their work provides initial inspiration for our study. Moreover, their findings suggest that compliance dynamics can be influenced by social factors, which aligns closely with our focus on the role of Theory of Mind (ToM) in compliance.
While SEIR models [HPS20] attempt to capture infection dynamics by dividing the population into Susceptible (S), Exposed (E), Infectious (I), and Recovered (R) compartments, these models, however, do not address the psychological and social reasoning processes that underlie compliance behavior. Our study diverges by focusing not only on pandemic modeling but also on the impact of individuals' social reasoning, driven by varying levels of ToM, on compliance. In addition, SEIR models are very generic and thus, for our study, we attempt to model our own simplified dynamics of the transmission probability. We plan to implement a similar model to that of SEIR, with individual agents having a status of either healthy, infected or immune (recovered).

2 Methods

To design a multi-agent system capable of simulating a pandemic scenario where agents act based on motives, we attempt to simplify our overall model as much as possible to provide a fundamental starting point for future research. The model focuses on two key components: disease transmission and compliance behavior.
As noted earlier, SEIR models are fundamental mathematical models designed to replicate the complexity of real-world COVID-19 scenarios. In our case, we implement a simplified formula for transmission probability, which is likely sufficient given that our focus is on compliance with Theory of Mind. The core idea of our model is that each healthy agent can get the disease from infected agents within a certain radius.
The compliance model can be considered the core strategy of each agent in the grid. Unlike typical multi-agent systems that rely on bonuses and penalties, we use basic stochastic functions that account for the surrounding environment. This approach remains within the agent's scope, as agents still perceive and interact with their environment. We incorporate the Theory of Mind (ToM) concept, where 0th-order agents follow a default strategy based on environmental parameters and internal states to decide whether to comply. Higher-order agents then estimate the majority's strategy for lower-order ToM agents to decide their compliance.

2.1 The Model

The model was developed in NetLogo [Wil99], because it allows you to easily simulate a large population of individual agents, each with their own behavior patterns and interactions with other agents. This is necessary so that all agents can decide for themselves what to do and we can then examine the outcome of all interactions. This model simulates the spread of an infectious disease within a population of agents and examines the influence of compliance behavior based on different behavioral levels, or Theory of Mind (ToM). Each agent can become infected, become immune or recover, while interacting with other agents in the environment.

2.1.1 Global and Agent-Specific Variables

In the model, there are global variables, such as Infection rate (I), Regulation strictness (R) and Initial willingness to comply (C). In addition, there are alpha and gamma parameters that indicate the strength of various motivations. This is further elaborated in section 2.3. Each agent has its own set of characteristics, namely their health status, whether they are compliant and the amount of social pressure. In addition, each agent has a ToM level (0, 1, or 2).

2.1.2 Visual Representation of Agents

The interface of the model is shown in Figure 1. The appearance of the agents shows their infection status and whether they are compliant. Their appearance changes dynamically based on these properties. The color of their face indicates the infection status: yellow means healthy, red means infected, and green means immune. The facial expressions also change. An agent that is healthy or immune looks happy, and an agent that is infected looks sad. When an agent is compliant, it wears a mask. This makes it clear which agents are compliant and which are not. When agents are infected or immune, they can still comply and therefore wear masks.

The agents move around in a semi-random way in the environment, making a random rotation of up to 45 degrees with each step and moving forward one step. This random movement causes agents to constantly interact with each other, which results in realistic interaction patterns compared to if they were to walk completely randomly or just straight ahead. When an agent is compliant, it actively keeps its distance from other agents to avoid infection. When another agent comes within a radius of 1.5 units of him, he moves in the opposite direction. This agent then adheres to the 1.5 meter rule that was used in the Netherlands during the pandemic, which contributes to reducing the transmission of infection within the population.

2.1.3 Infection Spread and Immunity

Infected agents can infect other agents within their immediate vicinity. The probability of infection is determined by the distance to infected neighbors, compliance behavior, and the number of infected neighbors. The infection spread is explained in more detail in section 2.2. When an agent is infected, it remains infected for 120 to 240 ticks, which is equivalent to 5 to 10 days, because each tick represents 1 hour in the model. Agents that recover become immune for 720 ticks, which is equivalent to 1 month, after which their immunity decreases and they become susceptible to infection again. These values are based on the reality of COVID-19 infections.

2.1.4 Compliance Strategies

Based on the Theory of Mind ordering issued to them, the agents employ various ways to determine their level of compliance. The model will take into consideration more of the various agent's desires and perceptions as the order of ToM increases. As further explained in subsection 2.3.2 agents equipped with zero-order ToM base their compliance on a simple basic strategy and only reason on an empirical basis without making assumptions. First-order order ToM agents and second-order ToM agents, unlike their simplest form, relate and work in cooperation with a Belief Desire Intention model. The latter, as the name suggests, is a model which dictates the importance of an agent's belief and desires providing the basis to formulate its intentions. Agents' intentions can be of two types: either comply and respect the guidelines or free-ride. The main difference between the two higher ToM orders is the way their agents relate to their peer. First-order order ToM agents look at their surroundings and takes into consideration their immediate environment characteristics when calculating the compliance probability. Second-order order ToM agents evaluate their surroundings but they also take into account other agents belief about them emphasizing the influence of social norms and perceptions. A more in-depth look on how compliance work is presented in Subsection 2.3.

2.1.5 Interface of the Model

The interface of the model, as shown in Figure 1, provides an overview of the main controls, parameters, and visual indicators that support the simulation. The sliders below the controls allow the user to adjust various parameters, such as:

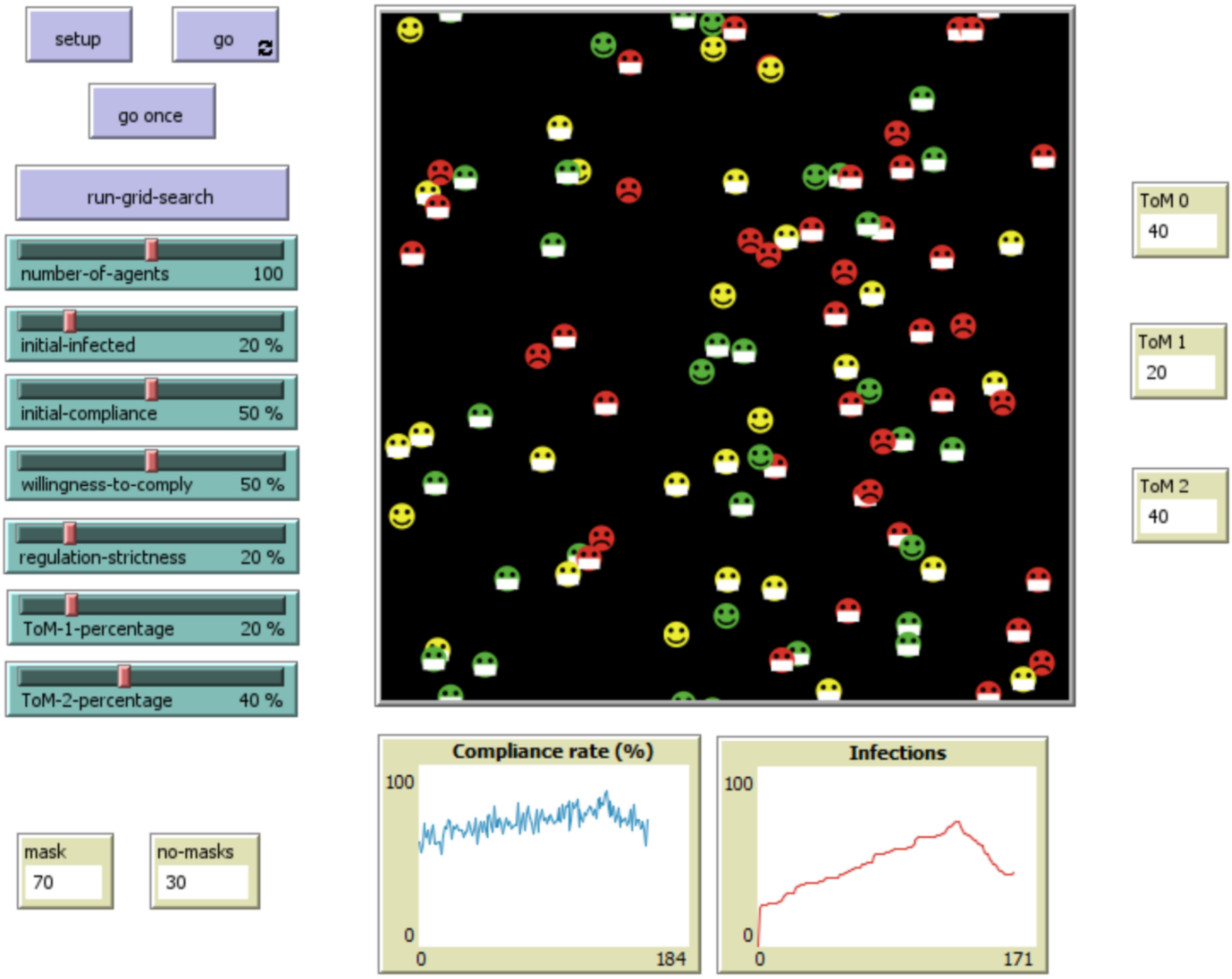

Figure 1: The interface of the model with the agent environment, adjustable variables, and compliance and infection rate graphs.

- **Number of agents**: The total number of agents in the simulation.
- **Initial infected**: The percentage of agents that are infected at the beginning.
- **Initial compliance**: The initial percentage of agents that comply with the rules.
- **Willingness to comply**: The willingness of agents to comply with the rules, which affects their probability of compliance.
- **Regulation strictness**: The strictness of the measures, which can also affect the probability of compliance.
- **ToM-1 percentage**: The percentage of agents that have first-order theory of mind.
- **ToM-2 percentage**: The percentage of agents that have second-order theory of mind.

The world is made up of 101 by 101 patches and is wrapped horizontally and vertically. This allows agents that reach the edge of the screen to re-spawn on the other side. This creates a continuous space where the agents can move freely, making it more realistic.

At the bottom of the interface are two graphs: the Compliance rate graph and the Infections graph. The compliance rate graph shows the percentage of compliant agents over time. It provides insight into how compliance changes as the simulation progresses. The infections graph shows the number of infected agents over time. It helps to observe the peaks and valleys in the infection rate, as well as the impact of compliance on the spread of the infection. In addition, statistics are shown on the number of compliant (wearing a mask) and non-compliant (not wearing a mask) agents, as well as the number of agents per ToM level (ToM 0, ToM 1, and ToM 2). These values provide a clear overview of the group composition based on compliance and ToM levels.

2.2 Infection Spread Model

Multiple factors might affect an agent's chance of getting infected by the virus. Researchers have proposed different ways to model the virus transmission. While some studies perceive agents as a whole, others have aimed to consider individual heterogeneity and implement a micro-crowd focus on each agent. [Lv+21] These theoretical models aim at a realistic approach in computing the transmission probability. Since we focus more on the compliance level, we attempt to reasonably simplify the formula. Therefore, we justify simplicity, based on the following reasons:

- There is a core focus on agent compliance with ToM. While we also observe the infection spread, the objective is not to flatten it or prevent its increase.
- We seek for a balance between realism and computational efficiency.
- We directly model infection based on the specific guidelines we are using as compliance factors; social distancing and mask-wearing.

To compute the total infection probability for a specific non-infected/negative agent, we construct a theoretical model that takes into account the agent's mask status, the number of infected agents around, and their distance from the agent. We first compute the probability of transmission by a single infected adjacent agent. We will refer to it as Individual Infection Probability (IIP). Then we will apply an additional function for the final transmission probability by N adjacent agents.

2.2.1 Probability of Transmission by a Single Infected Adjacent Agent

To calculate the IIP, we subtract a constant value from a power factor; a custom metric that expresses an agent's level of safety against the virus. The power factor is directly related to the agent wearing a mask, and the distance from the infected agent.

$$\text{Power Factor} = \text{Mask Factor} \times \text{Distance Factor} \tag{1}$$

The Mask Factor is a binary function, simply representing whether the agent is masked or not. These specific values are not important to our research question, they just represent mask or no-mask.

Mask Factor Value		Compliance Status
0.750	←	Masked
0.375		Unmasked

The distance factor is proportional to the Euclidean distance from an agent A to an agent B.

$$\text{Distance Factor} = 1 - \left(\sqrt{(A_x - B_x)^2 + (A_y - B_y)^2} + 1\right)^{-1} \tag{2}$$

Thus given (1) and (2), in order to compute the Power Factor we can use the following function.

$$PowerFactor = M\left(1 - \left(\sqrt{(A_x - B_x)^2 + (A_y - B_y)^2} + 1\right)^{-1}\right) \text{ with } M \in \{0.750, 0.375\} \tag{3}$$

To reduce the computational load, while also being practical, we allow only infected agents inside a Euclidean *radius* of 2 to partake in calculating the infection probability. In other words, infected agents are not able to transmit the virus to an agent more than 2 distance units away.
We can now obtain the maximum power factor since we know the maximum distance, and thus we know both the maximum distance factor and maximum mask factor. Since we want our IIP to be non-negative at all times, all we have to do is calculate a constant that can not possess a value below the maximum power factor. We can set our minimum IIP to a value of 0.1 (meaning the negative agent is masked, and its infected adjacent agent is located at 2 distance units away) and calculate our desired constant.
Given two agents A and B, we can define the IIP as follows:

$$p1(A, B, M) = \left(0.1 + \max_{PowerFactor(A,B,M)}\right) - PowerFactor(A, B, M) \tag{4}$$

where 0.1 is the Minimum Individual Infection Probability value. Since the Maximum Power Factor is 0.5, the constant we will use for our formula is set to 0.6.

$$p1(M, distance) = 0.6 - PowerFactor(M, distance) \tag{5}$$

2.2.2 Probability of Transmission by N Infected Adjacent Agents

To finalize our model, we make the following 2 assumptions:

1. Only the minimum distance affects the probability. Thus, from all the infected adjacent agents (within a radius of 2), we only take into account the agent's distance which is minimum. This is because we have already calculated a distance factor for our IIP and it would complicate our model if we tried to incorporate more than one distances.

2. We do not consider an infected agent's mask status to affect the chance of virus transmission. Mask status only plays a major role for the negative agent. This is also for mathematical simplicity.

Assuming a Grid-Space scenario and considering the *radious* used is equal to 2, there would be 12 tiles that could host an infected agent that can partake in the virus transmission. Assuming all twelve tiles are filled then there would be four agents for $d = 1$; four agents for $d = \sqrt{2}$ and four more agents for $d = 2$. We will utilize a Continuous-Space however, but can still simply include each infected agent within the specified radius. Thus, knowing the upper limit of agents that can transmit is more complicated, so we make sure our transmission probability converges for 12 adjacent agents.
Since we have the IIP, we can apply an additional function, so that the final infection probability also depends on the number of infected agents inside the defined radius. It is safe to assume that the more the infected adjacent agents, the more the curve increases. Again, we want the curve expressing the probability with respect to the number of infected agents, to converge, ideally around $N = 12$, and ensure it never exceeds the value of 1.
If we can compute a curve P which starts from the maximum IIP $\max_{p_O}$ and make it converge in a probability of $\max_{p_1}$, we get the maximum probability curve $P_{MAX}(N)$, and then we can substract the IIP difference between $\max_{p_O}$ and p0 to find the curve P for any other lower valued probabilities.

We set the maximum infection probability (converging threshold) to $\max_{pN} = 0.9$. Since $\max_{p_1} = 0.4125$, we can use the following formula to get the curve $P_{MAX}(N)$.

$$P_{MAX}(N) = \max_{pN} - (\max_{pN} - \max_{p_1})e^{\left(-0.3(N-1)\right)} \tag{6}$$

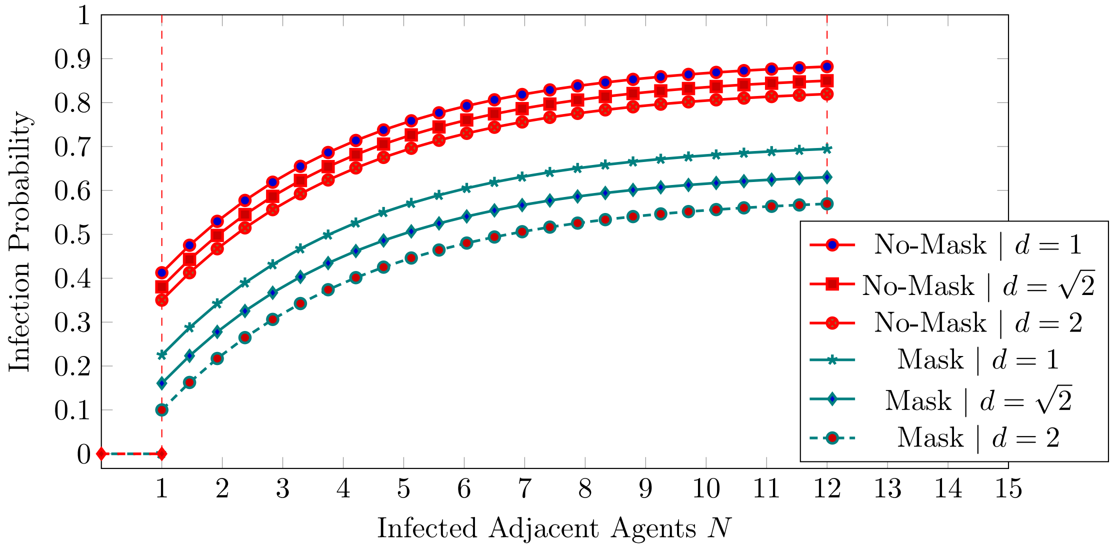

Figure 2: Plot showing the P curve for all possible Grid-Space scenarios within a $radius \leq 2$.

The exponential function is used to ensure convergence, with its factor experimentally set to -0.3. From (5) and (6) we have:

$$P_{\text{MAX}}(N) = 0.9 - 0.4875 \cdot \exp\left(-0.3 \cdot (N-1)\right) \tag{7}$$

Thus:

$$p(M, N, \min_{distance}) = P_{MAX}(N) - 0.4125 + p1(M, \min_{distance}),\ M \in \{0.750, 0.375\} \tag{8}$$

2.3 Compliance Model

During their evolution as a species, humans had to learn the hard way that not belonging to a social group would ultimately end in death. To comprehend the social environment, people have developed the ability to interpret both their own behaviors and those of others via the lens of mental states. The ability to understand others and interpret their minds in terms of intentional concepts such as beliefs, intentions, and desires is called theory of mind. Furthermore, theory of mind denotes the research field in which the ability to explain and predict one's own and others' behavior is studied [HVM12].
Theory of mind functions on several levels, enabling individuals to contemplate the motivations behind others' behaviors and to study the origin of one's intentions. Individuals can also employ this capability recursively, utilizing higher-order (at least second-order) theory of mind to deduce beliefs and objectives [Wee+15]. For Theory of Mind to function accurately, it is essential to represent an individual's mental state and its impacts; hence, a Belief-Desire-Intention (BDI) model is developed.

2.3.1 Belief Desires Intention model

The Belief-Desire-Intention (BDI) model is a widely-used framework in modeling decision-making and behavioral intentions within autonomous agents. It operates on the principles of three core constructs: beliefs, desires, and intentions, each of which plays a crucial role in simulating human-like reasoning and behaviors. Each order of Theory of Mind will have a slightly different BDI model in order to represent the more complex desires. Let A and B be two agents within the simulation.

- Given zero-order ToM agents then A does not investigate what others might do and focuses on external factors instead.
- Given first-order ToM agents then A estimates B's behavior and acts accordingly.
- Given second-order ToM agents then A estimates B's belief and intention and their impact on A, and acts accordingly.

The general BDI model of an agents is constructed as depicted in Table 2.3.1.

2.3.2 Compliance Probability of a Primary Agent

For simplicity, we will refer to agents that lack the ability to reason with Theory of Mind (ToM) as **primary agents**. These agents consider several system parameters when deciding whether to comply with regulations. We identify four key factors involved in their decision-making process:

1. **Infection Percentage (I)**
2. **Willingness to Comply (C)**
3. **Regulation Strictness (R)**
4. **Health Status (H)**

This strategy can be categorized as a **global strategy**, as each agent knows the overall infection percentage I across the grid. The willingness to comply C serves as an input parameter that reflects each agent's initial inclination to adhere to regulations, expressed as an abstract probability. Regulation strictness R refers to the enforcement of the rules by an authority, including fines and punishments for non-compliance. Finally, health status H represents the agent's internal condition, which can be classified into three distinct categories: **infected**, **healthy**, and **immune**.

For our mathematical model, we also make some assumptions regarding their responses:

- **Immune agents** are not influenced by the current infection percentage; their focus is primarily on regulation strictness R and willingness to comply C.
- **Healthy agents** are more likely to comply with regulations when the infection percentage I is high, as they want to protect themselves from potential transmission.
- **Infected agents** are more likely to comply with regulations when the infection percentage I is low, as they want to prevent others from potential transmission.

Let $\{w_1, w_2, w_3\} = \{0.34, 0.33, 0.33\}$ be a set of weights, let I be the percentage of infected agents, let R be the regulation strictness and let C be the willingness to comply. Every probability is expressed on a percentage scale. For a given infected agent ($H = 0$) the compliance probability can be computed as:

$$p = w_1 * I + w_2 \frac{R(100 - C)}{100} + w_3 * C \tag{9}$$

Component	Description
	Beliefs
Environmental variables	The agent's belief formed by the perceptions about the surrounding environment. Namely Infection Percentage, Willingness to Comply, Regulation Strictness and finally the health status of the agent in question.
Perceived Neighbors Behavior	The agent's belief about the health risks presented by others. A higher perceived risk increases the likelihood of personal compliance. This belief is an exclusive feature of higher orders ToM (at least first-order).
Perceived Neighbors Beliefs	The agent's belief about its own impact over the surrounding agent's BDI reasoning. Agents are then more strategically aware and take into account how others perceive their behavior, thus making more nuanced social decisions. This belief is an exclusive feature of higher orders ToM (at least second-order).
	Desires
Remain Healthy and Avoid Infection	The agent's desire to stay healthy and minimize exposure to potential health risks.
Minimize Effort	The agent's desire to avoid the physical or mental effort associated with compliance, such as wearing a mask or following physical distancing guidelines.
Social Desires	The agent's desire to conform to the actions of others. This desire is born our of convenience for our simulation. A sufficiently realistic simulation that accounts for social norms and social gatherings that impose conformity on their participants—such as academic institutions—is difficult to represent. The social desire allows then for an agent to "feel" social pressures and consequently having a probability to conform to the majority's actions.
	Intentions
Whether to **Comply**	Based on its beliefs and desires, the agent forms an intention to comply with health regulations (i.e. wear the mask and respect social distancing).
Whether to **Free-Ride**	The agent may intend to rely on the compliance of others while avoiding compliance itself, especially if it perceives low personal risk or believes that others are compliant enough to mitigate overall risk.

Table 1: Beliefs, Desires, and Intentions in the BDI Model used to dictate Theory of Mind agents reasoning.

whereas for a healthy agent ($H = 1$) the compliance probability can be computed by inverting the sign of the first weight w_1. This is measure is needed because it makes compliance important for healthy agents but further highlights the importance of the regulation for infected agents.

$$p = -w_1 * I + w_2 \frac{R(100 - C)}{100} + w_3 * C \tag{10}$$

For immune agents ($H = 2$), the first weight w_1 is set to zero, simplifying the compliance probability to:

$$p = w_2 \frac{R(100 - C)}{100} + w_3 C \tag{11}$$

We then ensure that the weights are equal for each summation factor. The exact values of the weights are not critical, as we perform standardization at the end.
The standardization formula is given by:

$$p' = \frac{p + 100}{200} \tag{12}$$

where p' represents the standardized probability.

In Figure 3 we show some probability distributions for different parameters in the 3D space. Two parameters are fixed: one refers to the agent's health status, while the vertical axis always represents the final compliance probability. It is important to note that the difference in maxima and minima for different health states should not be given excessive emphasis, as the model serves only as a simplified representation of behavioral motivations.

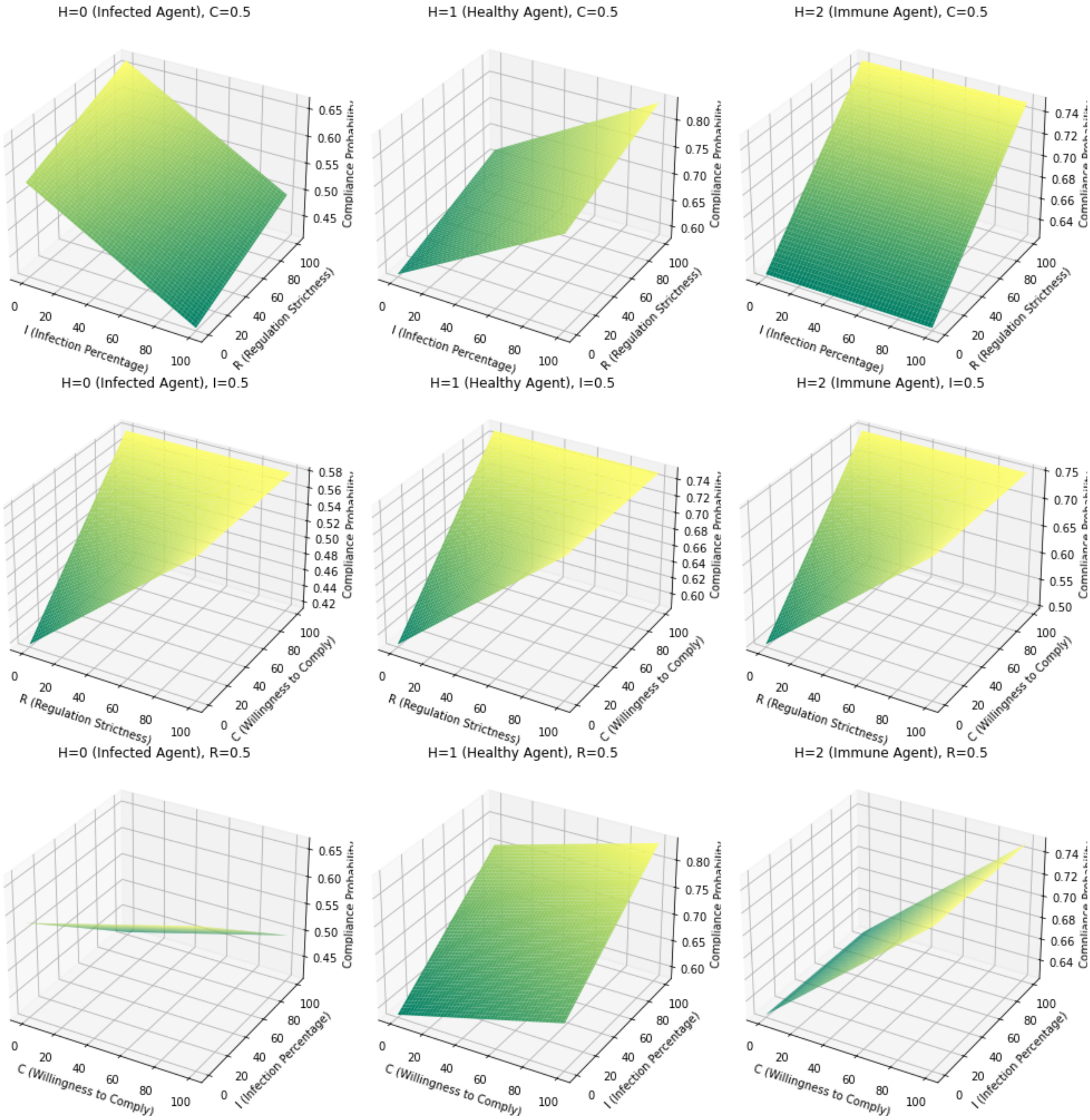

Figure 3: Compliance Probability for Different Parameters and Health-Statuses. The weights are 1/3 for the default strategy.

2.3.3 Compliance probability for Agents with Theory of Mind

zero-Order ToM Strategy The default strategy for primary agents was shown before. It does not utilize any form of reasoning beyond basic parameters. H_{primary} is the health status of the primary agent. It can be expressed as:

$$S_{\text{primary}}(I, C, R, H_{\text{primary}})$$

first-Order ToM Strategy Let $\beta = \{\beta_0, \beta_1, ..., \beta_n\}$ and $\gamma = \{\gamma, \gamma_1, ..., \gamma_n\}$ be two set of weights for beliefs and desires respectively. Let D_H, D_E and D_S represent the agent's desires and be defined as:

D_H **Desire to remain healthy** Calculated based on infection rate (I) and health status (H).

$$D_H = \alpha_1 \times I + \alpha_2 \times (1 - H)$$

D_E **Desire to minimise effort** Represents the desire to avoid compliance effort. This is higher when regulations are lax $(1 - R)$, or others are already complying (C).

$$D_E = \alpha_3 \times (1 - R) + \alpha_4 \times (1 - C)$$

D_S **Desire to be social** Agents want to comply if others comply. It depends directly on perceived compliance by others (C_O).

$$D_S = \alpha_5 \times C_O$$

Then the strategy for an agent equipped with first-order Theory of Mind can be defined as:

$$P(W = 1|I, R, C, H, C_O) = \frac{1}{1 + e^{-(\beta_0+\beta_1 I+\beta_2 R+\beta_3 H+\beta_4 C+\gamma_1 D_H-\gamma_2 D_E+\gamma_3 D_S)}}$$

where W represents the compliance (i.e. Wearing a mask), I, R, C and H are the core beliefs of the agent and C_0 is the perceived compliance by others. The function leverages a logistic model in order to obtain a probability ($P(W = 1)$) of the agents compliance. Given a normal distribution $\mathcal{N}(0, 1)$ an agent will be compliant where

$$P(W = 1|I, R, C, H, C_O) \leq \mathcal{N}(0, 1)$$

second-order ToM Strategy A second-Order ToM agent extends the first-order by considering not only what others are doing but also "what others think about it". This introduces a recursive level of reasoning, where agents make decisions based on perceived beliefs about themselves.

Let $\beta = \{\beta_0, \beta_1, ..., \beta_n\}$ and $\gamma = \{\gamma, \gamma_1, ..., \gamma_n\}$ be two set of weights for beliefs and desires respectively. Let D_H, D_E and D_S represent the agent's desires the same way they do for first-order ToM. Let B_S represent the perceived beliefs about self and be defined as:

B_S **Belief about Self** This belief models how agents alter their behavior in response to what they perceive others think of them. Agents are therefore more strategically aware and consider how others perceive their actions, resulting in more sophisticated social judgments.

$$D_B = \gamma_4 \times B_S$$

Then the strategy for an agent equipped with second-order Theory of Mind can be defined as:

$$P(W = 1|I, R, C, H, C_O, B_S) = \frac{1}{1 + e^{-(\beta_0+\beta_1 I+\beta_2 R+\beta_3 H+\beta_4 C+\gamma_1 D_H-\gamma_2 D_E+\gamma_3 D_S+\gamma_4 D_B)}}$$

2.4 Simulation Process

The research question in this study is: How does Theory of Mind impact compliance rates with public health guidelines in a simulated pandemic environment? To answer this question, we test different levels of theory of mind, namely zero-order, first-order and second-order, and investigate their influence on compliance and infection rates within the simulation. Five simulations are performed for each combination of ToM levels. There are combinations where only one level is present (100% for ToM-0, ToM-1, or ToM-2), two levels are evenly split (50% for each pair), and one scenario where all three levels are equally represented (33% each).

In addition to theory of mind, the influence of regulation strictness is also investigated, while the other parameters are being tested and averaged throughout a grid search. The number of agents is tested in a range of 10 to 100 agents with steps of 10. The variable 'Initial infected' is tested from 5% to 60% with steps of 5%. This was chosen because with values higher than 60% all agents are infected within no time and then immune, which immediately stops the simulation. The 'Initial compliance' is set to 50%. This parameter is used solely for initialization and does not significantly impact our analysis. The variable 'Willingness to comply' is set to values in a range of 20% to 90% with steps of 10%. Then 'Regulation strictness' is set either to 0 or equal to the 'Infection rate (I)' to simulate a dynamic regulation scenario, meaning with more infected agents, the regulation becomes stricter. This makes it more realistic. An overview of these variables and values is shown in Table 2.

Variables	**Value**
Number of agents	10 - 100
Initial infected	5% - 60%
Initial compliance	50% (constant)
Willingness to comply	20% - 90%
Regulation strictness	0% (no) and I (dynamic)

Table 2: Overview of model variables and values.

For each combination of theory of mind levels, 5 simulations are run. During each simulation, all ranges of the other variables are tested. Furthermore, within each simulation, a number of values are collected at each time (or 'tick'), namely the values of all variables, combination of ToM, and the resulting 'Infection rate' and 'Compliance rate'. These data are stored per tick in a csv file, which creates a detailed picture of how compliance and infection develop over time.
After running the simulations, the data is analyzed to gain insight into the effect of different ToM levels on compliance and infection behavior.

3 Results

This section presents our final results with the comparison of infection and compliance rates across two scenarios: Scenario 1 (parameter $R = 0$) and Scenario 2 (parameter $R =$ Infection Rate).

3.1 Infection Rate

The mean infection rate was similar across both scenarios, with Scenario 1 showing a mean of 23.59 (SD = 21.54) and Scenario 2 showing a mean of 22.52 (SD = 21.23). A t-test yielded a high t-statistic ($t = 105.58$, $p < 0.00e + 00$), indicating a statistically significant difference, possibly due to the large sample size. However, in practice the difference in infection rates is small. Therefore, applying dynamic regulation has only a small impact on reducing the infection rate. While we should expect a higher correlation magnitude in a real-world application, the results still suggest that the goal of keeping the infection spread low is accomplished in both scenarios.

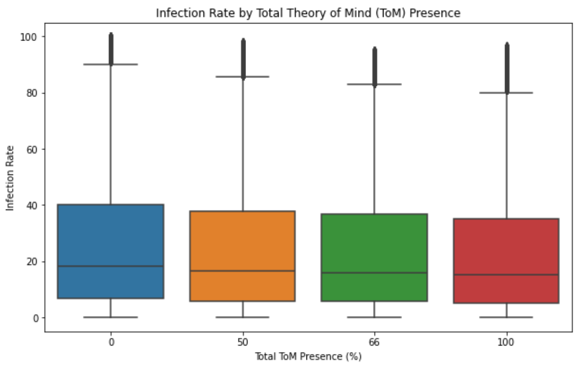

Figure 4: Infection Rate with Theory of Mind Presence (No Regulation)

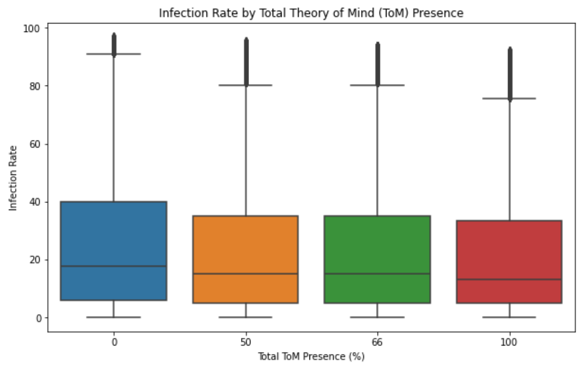

Figure 5: Infection Rate with Theory of Mind Presence (Dynamic Regulation)

In Figures 4 and 5 we can observe that theory of mind presence results in lower infection rate median values.

3.2 Compliance Rate

We observed a great difference in compliance rates between the two scenarios. Scenario 1 showed a mean compliance rate of 56.11 (SD = 15.52), while Scenario 2 exhibited a much higher mean of 85.27 (SD = 14.33). The t-test results ($t = -4169.44$, $p < 0.00e+00$) confirmed this difference as statistically significant. The large mean difference implies that setting R to the Infection Rate in Scenario 2 has a meaningful positive effect on compliance levels.
As shown in Fig. 6, we can derive that ToM agents exhibit more unpredictable behavior compared to 0-th order ToM agents, with a tendency to free-ride more frequently. In Fig. 7, we observe that ToM agents demonstrate high compliance across nearly all cases, whereas regulation strictness appears to have minimal impact on the compliance of 0-th order agents.

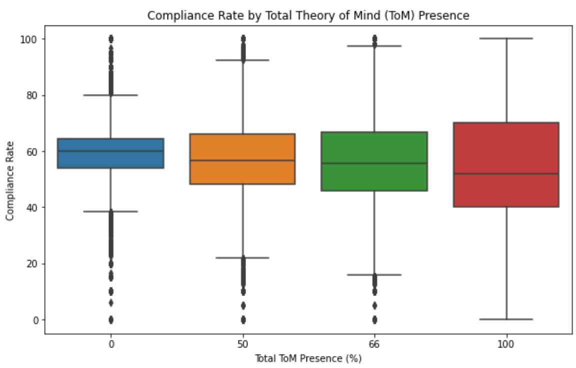

Figure 6: Compliance Rate with Theory of Mind Presence (No Regulation)

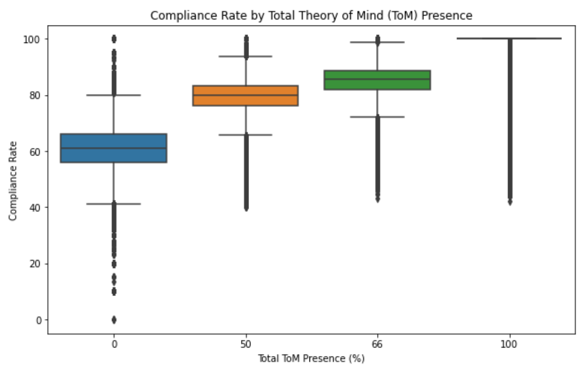

Figure 7: Compliance Rate with Theory of Mind Presence (Dynamic Regulation)

4 Discussion

This study investigates whether Theory of Mind (ToM) influences compliance. The results show that when no regulations are applied, various factors can lead ToM agents to choose compliance almost at all times. However, they also exhibit a tendency to free-ride when stricter regulations are set. Typically, it would be expected that an agent would free-ride more when regulations are absent, and ToM agents display this behavior clearly. When regulations are enforced, they tend to comply at consistently high levels, much more than 0-th order agents. This is likely due to a strategic behavior that showcases their adaptive compliance.

It was also observed that as the presence of ToM agents increased within the grid, infection rates tended to decrease, though slightly. This could reflect the adaptive behavior, as perhaps they subconsciously aim to reduce infections and meet the common goal by complying.

For ToM agents, considering others' mental states and perceiving what others might think about them might be interpreted in a lot of ways. In the absence of regulations, ToM agents may infer that others are likely to comply less and might seize the chance to do the same. Being aware of real-time infection rates, these agents may selectively free-ride, possibly assessing lower infection periods as safe opportunities to mimic the potential non-compliance of others. On the other hand, when dynamic regulation is applied, ToM agents appear to anticipate greater compliance from others and thus align their behavior to match these expectations.

Ultimately, one can infer that ToM results in slightly lower infection rates, as agents with ToM adapt their compliance to help maintain a low infection rate. They can adapt their compliance depending on the scenario in order to meet the common objective, highlighting the importance of incorporating Theory of Mind in cooperative scenarios. This also highlights the value of studying its application in practical cooperative situations, such as COVID-19 pandemic, which merits further exploration.

4.1 Limitations

Unfortunately, this study also has some limitations that need to be acknowledged. The Infection Spread Model is simplified and does not fully capture the complexity of real-world transmission dynamics. It does not take into account exposure time or the spaces in which the agents are located, which has a major impact on infection spread. Although NetLogo is so easy to use due to its simplicity, it also has disadvantages. The model is not realistic enough to simulate the real world. The environment would have to be much more complex and many more agents would have to be used. Also, the behavior of the agents is now completely based on rules and does not take other factors into account, see Future Research. Finally, the compliance update should be improved. The agents now decide for every tick whether or not to comply, while in reality someone would not change their mind every hour.

4.2 Future Research

The simulation results provide several opportunities for future research to improve the realism and applicability of the model. First, future models could include variables such as vaccination status, social background and agent memory. These factors would also influence the ToM of the agents and play a role in real life. Furthermore, incorporating recent survey and experimental data could make the compliance probability more accurate and realistic by better reflecting human behavior. Another thing that could improve the model is creating a more realistic world where people can be in rooms, which increases the chance of infection. Finally, it would also be interesting to apply reinforcement learning where the agents learn from their choices and the environment, making them increasingly smarter. This would introduce an element of long-term behavior change, reflecting how real populations adapt to long-term public health crises.

5 Conclusion

Overall, the findings of this study confirm the importance of Theory of Mind in cooperative compliance scenarios. ToM agents adapt their behavior to align with infection control goals, indicating that raising social awareness and implementing adaptive regulations may be effective strategies for ensuring compliance. Future research could extend these insights and investigate additional parameters and adaptive behaviors to increase knowledge about compliance dynamics in complex social systems.

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