Delft University of Technology

Master Thesis

Modelling an Emergency Evacuation

Mathematical modelling of emergency evacuation in the presence of search and rescue robots: A combined game theoretic and BDI-based approach

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Laura Wilmes
(5234042)

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Graduation Committee

Dr. Anahita Jamshidnejad
Dr.ir. Coen de Visser
Dr. Trivik Verma

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Executive Summary

The impact of disasters on the affected population are catastrophic and disruptive. Proper disaster management practices are therefore needed to reduce the societal damage they induce. This report therefore aims at reviewing the literature in the field of disaster response. A focus is set on Search and Rescue (SaR) missions, which are a part of the emergency response and include measures to find victims. These activities are undertaken mostly by first responders and rescue workers. The environment in which rescue workers need to operate is highly complex, dynamic and hostile. In an indoor evacuation scenario, these rescue workers risk their own lives in order to find trapped victims. Their task can be alleviated by the support of a fleet of robots. This fleet is deployed to locate trapped victims and to report back their position to the emergency responders and if necessary to follow them in order to keep track of their potential movements. Locating trapped victims is challenging as the number of these people as well as their initial position and potential displacements may be unknown. A behavioural model of the victims is needed to give insight how they take decisions and accordingly act during an evacuation situation. For this, several techniques have been reviewed, including agent based modelling, the belief-desire-intention framework, and game theory. Agent based modelling proves itself well for capturing the microscopic interactions between victims that give rise to a global pattern. The belief-desire-intention framework is able to add emotional and cognitive elements within the behaviour of the victims. Game theory can be used to provide additional insight into individual and collective decision making processes. This study then evaluates the construction of a model that incorporates these elements. A use case is presented, constituting of an indoor evacuation setting, with which the model is validated against a benchmark from the available literature. In this model, evacuation robots are added and their influence on human behavior analysed. Thus, this research contributes to the state-of-the-art of SaR operations with a validated model of human decision making during indoor evacuation settings, with and without the presence of evacuation robots, by combining two exiting methods in a novel way. With this model, a more effective planning of SaR operations can be achieved, and an understanding gained into how the presence of rescue robot might affect human decision making.

Acknowledgments

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Laura Wilmes
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Contents

Nomenclature

ABM Agent-based model

BDI Belief desire intention

GNSS Global navigation satellite system

GT Game Theory

SaR Search and Rescue

UAV Unmanned aerial vehicle

UGV Unmanned ground vehicle

List of mathematical symbols

a	Amplifying evacuation factor
b_d	Belief dangerous
c	Compliance factor
$d_e(t)$	Desire evacuate
$o_s(t)$	Observation staff instructions
$o_a(t)$	Observation public announcements
S	Given coalition as a subset of players
N	Set of players in a game
$x(S)$	Payoff vector of coalition S
v	Characteristic function of a game
$v(S)$	Total value of coalition S
$v(N)$	Total value of the grand coalition
$e(S, x)$	Excess value of a coalition S spending on payoff vector x
$s(a)$	Maximum speed of agent a
$G(a)$	Group of which agent a belongs to
$V(a)$	Group which agents a chooses
λ	Weighting factor for group choice
$P_i(st_i, ..., st_n)$	Payoff of player i based the set of strategies $(st_i, ..., st_n)$
$T_i(i_c)$	Estimated evacuation time of agent i depending on its neighbors (i_c)
N_{i_c}	Number of neighbors of agent i
$\delta u(T_i(i_c))$	Change in utility due to conflict
t_d	Conflict cost
r_j^{exit}	Position of exit j
$\Delta u_{il}(k)$	Utility due to conflict between of agent i depending on conflicting agent l
$d_{ij}(k)$	Distance covered at each iteration t by agent i
$v_i(k)$	Velocity of agent i at time t
t_d	Duration of conflict

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1 Introduction

The word 'Disaster' is derived from the ancient greek words of 'dus' and 'aster', meaning bad star and connoting to an unfortunate fate. This implicates already one of the most tragic characteristics of disasters, namely that they cannot be prevented (Khorram-Manesh et al., 2021). Fires and earthquakes have plagued ancient and modern populations alike and disasters, natural or human-instigated, more often than not have devastating consequences. Recent examples of disasters include the collapse of buildings in Florida in 2021 and Changsha in 2022, each having caused dozens of casualties (Dalvin Brown Washinton Post, 2021; Reuters, 2022).

The United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) estimates that due to disasters and emergencies around 275 million people will need humanitarian assistance which corresponds to 1 person in 29 worldwide (UNDRR, 2022b). Hence it is imperative to be timely to respond to the disasters in order to mitigate detrimental consequences. When a disaster occurs, very early in the disaster response, search and rescue (SaR) missions are performed, during which rescue workers and first responders need to be quick to secure the site of the disaster, locate victims and rescue them from the potential risks. The decisive factor for the success of SaR missions is often the speed with which rescue workers are at place and can conduct SaR missions (Murphy, 2004). With technological advancements in various fields such as in robotics, sensoric, and autonomy, the field of SaR robotics has emerged. SaR robots can alleviate the task of rescue workers and support them in both finding and potentially saving the located victims from the disaster scene. Robots prove themselves helpful to assist in these tasks for various reasons. To name only a few, robots are expendable, they can participate in tasks that are hazardous for human rescue workers and finally, depending on the extent of their autonomy, can take decisions at a much higher speed (Murphy, 2004).

Disaster scenarios are highly complex. The environment is dynamic and people interact with each other in order to get themselves to safety. The behaviour of trapped victims can further increase the tragedy of disasters. A recent example is a soccer game in Indonesia, where around 125 people died due to stampedes, which resulted from people trying to evacuate from the soccer stadium (NY Times, 2022). Understanding how humans interact in a multi-actor setting can be a decisive factor for efficiently planning a SaR mission (Robin and Lacroix, 2016). Different people have different intentions during a disaster, based on individual goals. Some people might be willing to cooperate with others, while others will focus only on getting themselves out of an emergency setting (Van der Wal et al., 2017). Modelling and simulating human decision making is therefore a first step in order to be able to ultimately predict or at least estimate how people could behave during an evacuation. As such, these predictions have the potential to further increase the speed of SaR mission.

The report is structured as follows. To begin with section 2 provides the motivation for this project and presents the research question that this study aims at answering. Then, Part I represents the literature survey that was conducted. The reviewed literature, starting with section 3, will be used to identify a knowledge gap and to propose a model structure to model multi-actor interactions for indoor evacuation scenarios together with a benchmark in section 5 which will be implemented in a use case in Part II. Finally, in part III section 7, conclusions are provided as well as some recommendations for further research that were identified during this project.

2 Thesis Project

In this section, the motivation for the research in this project is outlined. Then, the research objective and main research question are given. The main research question is further broken down into several sub research question that help addressing the main research question and are answered in the remainder of this report.

2.1 Research Motivation

Disasters cannot be prevented and therefore it is imperative to have emergency response procedures in place. To alleviate the task for first responders of SaR missions, these have been using SaR robots during operations in the past. While a lot of research is being conducted in how to improve the technological aspects of these robots, the human aspect and more specifically, how the presence of these robots might affect the behavior of the victims, is overlooked.

A behavioural model of the trapped victims can be helpful for mission planning of SaR operations. From reviewing literature about available tools to do so, it can be concluded that many different tools are available to model human decision making. However, all of these tools have their drawbacks and further research is needed for incorporating as many elements of human decision making as possible for a simulation model to be realistic. Thus, implementing a combination of tools such as Agent-Based-Modelling, the Belief-Desire-Intention (BDI) and concepts of game theory promises to reflect human decision making in indoor evacuation scenarios: reflecting the cognitive and emotional reasoning processes of humans but also explain individual and collective rationality when making joint decisions.

Furthermore, no existing evacuation model is implementing SaR robots. Thus, no model is capable of simulating the affect of their presence on human behavior during evacuations. Such a model would allow to examine how SaR robots can be best employed to assist in rescuing victims from an emergency setting.

2.2 Research Questions

Resulting from this, the research objective of this thesis is to create a simulation model of an indoor evacuation scenario that captures human behavior in the presence of SaR robots. For this, different existing modelling tools will be combined to capture human decision making as realistically as possible. Evacuation robots will be implemented in the model that will assist the humans to evacuate from the emergency setting. It is be assumed, that humans behave differently in the presence of evacuation robots and that the trust they have in these robots further influences their behavior around the robots.

Thus, the main research question of this thesis is: *How can human behavior during an indoor evacuation scenario be modelled in a simulation model in order to understand the dynamics of human decision making, with and without the presence of SaR robots potentially influencing human behavior?*

In order to answer this question, several sub research questions are needed that are answered in the different chapters of this report.

1. What are the elements of SaR missions and what is the role of SaR robots?

   (a) What are the objectives of search and rescue missions, and what are the challenges associated with these missions?

   (b) How can robots be effectively employed in SaR missions to enhance operational efficiency and increase the likelihood of successful outcomes?

   (c) In the context of indoor evacuation scenarios, how do evacuation robots interact with humans during the evacuation process?

2. How can human decision making during indoor evacuation scenarios be modelled and the resulting human behavior be simulated?

   (a) What tools are available to do so and what are their drawbacks and advantages for modelling and predicting human behavior?

   (b) What are the fundamental principles and components of the BDI framework and game theory concepts?

   (c) What are the key factors that influence human behavior during an indoor evacuation, and how can these factors be incorporated into the combined BDI-game theory model?

   (d) How can the BDI framework be adapted and integrated with game theory concepts to effectively capture the dynamics of human decision making during an indoor evacuation scenario?

   (e) How can the combined BDI-game theory model be validated and evaluated to assess its effectiveness in accurately simulating and predicting human behavior during an indoor evacuation scenario?

3. What is the effect of the presence of evacuation robots on human behavior in indoor evacuation scenarios?

   (a) What are the factors that influence human interaction with SaR robots during an emergency evacuation?

   (b) How does the presence of SaR robots influence human decision making and behavior during an indoor evacuation scenario?

   (c) How does the introduction of SaR robots affect the overall evacuation time and evacuation success rate in indoor scenarios?

These sub research questions help answering the main question and research objective and are answered subsequently in this report. The first and the second question are mainly addressed in the literature survey in Part I section 3, section 4, section 5 and section 6. The answers to these research questions are then used to build the combined BDI-game theory model and to validated it in the thesis paper in Part II. The third research question is also addressed in Part II. The discussion in Part III section 7 recapitulates these research questions and provides conclusions and recommendations for further research. Part IV Appendix A provides provides some further insights into model results that are not further discussed in this paper.

Part I

Preliminary Thesis Report: Literature Survey

3 Search and Rescue

This section introduces the field of Search and Rescue. First, the notions of disaster and disaster management are explained. Then, some examples of applications of robots for SaR are given. After this, a closer look is taken on SaR missions and their environment in which robots need to operate.

3.1 Disasters

Disasters have plagued humankind since ancient history. Disasters are defined as disruption to the functioning of society with losses and damages in every aspect of life from human, material, economic and environmental losses and impacts. The cause of disasters are hazardous event that are either natural or human made. Natural disasters could be volcanic disruptions or flooding, while human-made disasters include conflicts or traffic accidents (Khorram-Manesh et al., 2021).

The consequences of disasters and the resulting disaster damage depend greatly on the affected society's resilience, vulnerability and exposure to the hazards that the disaster has caused. The consequences of a disaster can be local and immediate or can be wide spread and last for longer periods of time. Often, assistance from outside of the immediately affected community is needed. Before an incident can be classified as a disaster, some criteria need to be met such as the death of at least 10 people, at least 100 people affected or the government declaring a state of emergency, amongst others. For making this distinction clearer, the difference can be made between the following types of disasters (Khorram-Manesh et al., 2021; UNDRR, 2022a):

- Small scale disasters, where a community is affected, which as a result needs assistance from external to the community.
- Large scale disasters affect a society as a whole, which consequently needs national or even global assistance.
- Slow-onset disasters develop gradually while the impacts and damages also develop over time and are not immediately visible.
- Sudden-onset disasters are triggered by one hazardous event.

The different phases of a disaster can be described as a cycle with a pre-disaster phase, the disaster phase and the post-disaster phase. In each other these phases, different measures are taken (Khorram-Manesh et al., 2021).

3.1.1 Disaster Risk Management

Since disasters cannot be prevented, there will always be a risk of a disaster taking place. Risk can be measured in various ways while the quantification of risk has its own limitations. Ultimately, a certain risk will have to be accepted. Figure 1 shows the acceptable risk region for civil engineering infrastructure projects in the Netherlands. The risk becomes unacceptable as soon as the number of fatalities is greater than 1000 and the frequency of these events exceeds 0.001 times per year (Faber and Stewart, 2003).

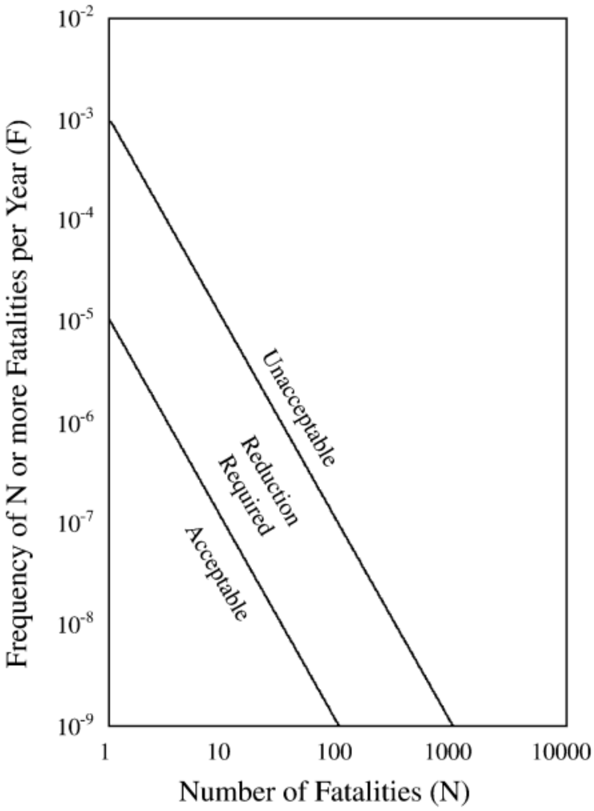

Figure 1: Target for societal risk in The Netherlands from (Faber and Stewart, 2003) for civil engineering applications

In order to reduce the risk of a disaster taking place, risk reduction measures need to be undertaken. These activities are be taken in order to keep the residual risk ”As Low As Reasonably Possible” (ALARP), see Figure 2 (Faber and Stewart, 2003). When speaking about disasters, these activities are termed disaster risk management (UNDRR, 2022a) before the actual occurrence of the disaster.

These aim at reducing the risk which a community or a society is exposed to a disaster. This includes the pre-disaster phases of prevention, damage mitigation and preparedness. However, as already pointed out, this risk cannot be fully prevented and there is a residual risk of a disaster happening (see Figure 2). To illustrate, after building a dam in the village to prevent the river from flooding houses and roads, there will still be the risk that the dam is not high enough and will still flood the village. This residual risk can be deemed acceptable or tolerable: Those people that still continue living in the village accept that this risk is tolerable (Khorram-Manesh et al., 2021).

Due to the residual risk which cannot be prevented using disaster risk reduction measures of the prevention phase, there needs to be contingency planning in order to ensure that emergency response capacities are available. This translates to the preparedness phase during which before the actual disaster measures are taken to arrange evacuation procedures Khorram-Manesh et al. (2021) while the aim of an evacuation is to protect people from hazards by temporarily moving them to safer places (UNDRR, 2022a).

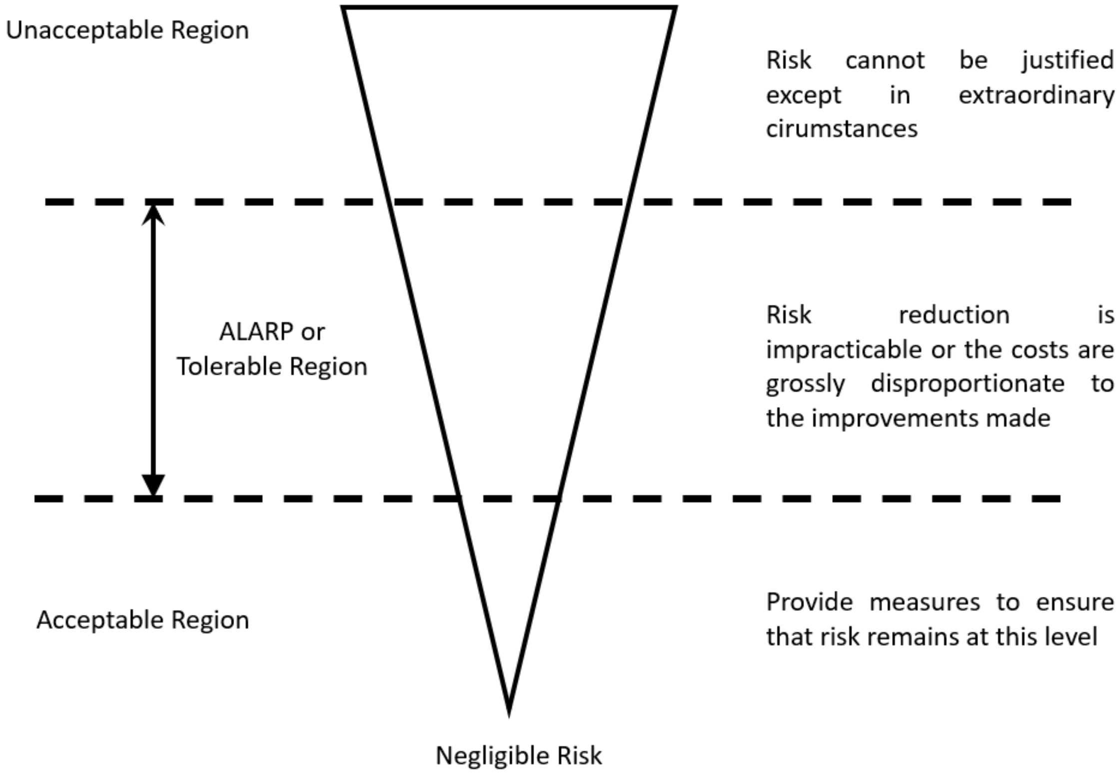

Figure 2: Levels of Risk from (Faber and Stewart, 2003)

3.1.2 Disaster Response

In the case where a disaster does happen, an emergency response or disaster relief is needed. These actions aim at ensuring public safety and protecting people from the impacts of the disaster. This is the phase where SaR actions are needed to look for survivors and meet the basic needs of the victims. Time is also crucial here as with an increased response time the survival rate of victims drops drastically during the first two days after a disaster (Barbera and Cadoux, 1991).

Finally, during the post-disaster phase, recovery actions are taken to "build back better". Here, infrastructure that has been destroyed needs to be build back. The aim of this stage is to avoid a new disaster from taking place by taking account of lessons learnt, hence to build what has been lost back in a better way, such that it is more resilient to potential future disasters (UNDRR, 2022a; Murphy et al., 2016).

On some occasions, robots have been deployed during or after disasters in the past (Murphy et al., 2016). In general, there remains an ethical question whether it is right or wrong to use a not yet fully mature technology during disasters. The next section gives a brief overview of what these applications look like and about the lessons learnt.

3.1.3 Use Cases of Robots for SaR

The terrorist attacks on the World Trade Center in 2001 are an early application of robots to a disaster scene for SaR missions. During this first deployment of robots, little "PackBots" as they were called were deployed to dig through the rubble of collapsed buildings. More specifically, they were entering into voids were neither humans nor dogs could enter due to their size and the lack of oxygen (Murphy et al., 2016).

In 2011, after the Fukushima nuclear disaster, airborne robots were deployed to check the nuclear plant for overheating. This was a task which humans could not because of the nuclear radiation (Vince Beiser Wired, 2018).

These early applications all included a human controller that was communicating with the robots over radio frequency using a joy stick. With greater advancements and more research programs into autonomy, human control can become less important. A couple of EU funded projects are ICARUS and DARIUS, both with a focus on autonomy to enhance the situational awareness for first responders and rescue workers (Govindaraj et al., 2013; Chrobocinski et al., 2012).

A more recent example of using robots in SaR missions includes the collapse of a building in Florida, USA a year ago in 2021. Here, robots were deployed to aid the SaR efforts to get through narrow passages and voids. Here, the employed robots were designed to be operating semi-autonomously, such that they could complete some tasks autonomously while others needed teleoperation (Dalvin Brown Washinton Post, 2021).

These real life applications of SaR robots show that, while they have in the past successfully located victims of disaster scenes, the environments in which they need to operate are very challenging. Thus, more research can greatly enhance the effectiveness of deployment of robots for SaR (Murphy et al., 2016).

3.2 Search and Rescue Missions

This section starts with the different types of environments robots encounter on their SaR missions. Then different types of SaR robots are introduced and their application in the disaster response explained.

3.2.1 Environments

The environments in which SaR missions are conducted depend on the circumstances of the disaster that has occurred. Generally, the distinction can be made between indoor and outdoor SaR missions.

Indoor environments are usually highly cluttered, especially in contrast to outdoor environments. To illustrate, in the case of a collapsed building, there is a lot of rubble and debris which impedes the visual sensory capabilities as well as object avoidance capabilities of robots. Dust and smoke from fire will further impede the robots from orienting themselves in the building. Moreover, global navigation satellite system (GNSS) might not be available for navigation inside of the building (Murphy et al., 2016). In addition, the environment is highly dynamic as new debris can fall from the destroyed building. As a result, trajectories that a robot had planned to employ might change due to debris being in the way. Moreover robots must be small enough in size to manoeuvre through the environment. This limits the computational capabilities of the deployed robots. Furthermore, an unknown number of victims is trapped in the building. While the victims are mostly considered to be stationary, they might still be locally moving while trying to get out of the disaster scene. This further complicated the mission planning for the robots. The danger to rescue workers are also the greatest in indoor environments, as there is a risk of fire spreading or more infrastructure collapsing (Murphy et al., 2016; Grogan et al., 2018; Khorram-Manesh et al., 2021).

Outdoor SaR environments can further be categorised into wilderness, urban and marine environments. The conditions in these vary to great extents. In general, outdoor environments are wider and less cluttered than indoor environments. Furthermore, they usually deal with a known number of victims that are mobile. In wilderness and marine SaR, there is mostly a given number of victims of which at least some initial position is often given. Navigation can also be easier as landmarks can help with orientation and the environment is not as cluttered. In addition, GNSS is mostly available and sensory capabilities are less impeded. However, meteorological uncertainties such as sudden heavy rainfalls or fog can affect the deployments of robots for SaR in outdoors settings (Murphy et al., 2016; Grogan et al., 2018).

3.2.2 Robots for SaR

Different types of robots can be deployed for indoor SaR missions. In general, unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV) can be deployed for indoor SaR missions. Two examples of such robots can be seen in Figure 3. Other robots that can be used for outdoor settings could be unmanned water surface vehicles and unmanned underwater vehicles, while their application for indoor settings are limited. In terms of size, these robots can be either man-packable if they fit into one or more backpacks, man-portable when they can still be carried short distances by one or more persons and maxi robots that have to be transported by vehicles (Murphy et al., 2016).

Land based UGV can be used to crawl over rubble. They have been used to enter and manoeuver into debris voids of less than 1 cm into which human rescue workers or dogs cannot enter, since the holes are too small and there is no oxygen available. (Murphy et al., 2016)

UAVs are exclusively airborne and have a high degree of freedom. They are generally classified into fixed wing and rotary UAV. Fixed wing UAVs lend themselves for covering wide areas and their application for indoors is limited as well due to the necessity of wind to create a lift force. Still, they can be deployed to gather information and greater situational awareness (Murphy et al., 2016).

(a) Rotary UAV can explore indoor environments (TU Delft, 2022)

(b) UGV are able to crawl over rubble (NIST, 2022)

Figure 3: Examples of different SaR robots

There are many ways in which a fleet of robots may be organised. A fleet can be composed of robots of the same type which then be a homogeneous fleet. A fleet can also be composed of robots with different capabilities, such as UAVs and UGVs.

The advantage of a homogeneous fleet is their scalability, flexibility and robustness. To illustrate, when having a fleet of the same UAV, there could always be more robots added to increase the size of the fleet, hence making it scalable. At the same time, it is flexible, since the loss of one or another UAV does not necessarily impact the performance of the fleet. On the other hand, a non-homogeneous fleet comprises robots of different types. The main advantage is that the (sensory) capabilities can be distributed over all robots of the fleet and not every robot needs to be equipped with the same sensory suite (Brambilla et al., 2013; de Koning and Jamshidnejad, 2022).

A fleet of robots, whether homogeneous or non-homogeneous, is referred to as a multirobot system. Different control schemes can be exploited for controlling it. Often used are modelled based control schemes that comprise a set of methods that need a model of the system to find the next control action. The next control action is determined using the prediction of future control actions based on the current state of the system. These methods can be distinguished into cooperative, distributed and decentralised methods (Rawlings et al., 2017).

3.2.3 Target Management

The SaR mission on which a fleet of robots is deployed pose many challenges due to the highly complex and dynamic environment in which they need to manoeuvre through. Another challenge is posed by actually defining the SaR mission. The goal of such a mission is to search and rescue for trapped victims in an indoor disaster scene. Hence, it can be described as a target management problem, where a target refers to a trapped victim (Robin and Lacroix, 2016).

Initially the focus is on actually finding victims within the disaster scene: Since the number of victims is usually not known and neither is their position, at the start, a SaR mission can further be classified as a target detection problem (left branch of Figure 4). As the mission involves moving robots rather than static sensors, it can be described as a mobile search, or path planning problem. As can be seen in Figure 4, this leaves four choices for search strategies: capture, hunting, patrolling and probabilistic search. These methods all have advantages and drawbacks. In the capture problem is to detect a target that is in a certain determined area. In the hunting problem, the detection and the capturing cannot be guaranteed, due to the lack of resources such as time or robots. Probabilistic search is different to the capture problem in so far that probabilities of detection of a target are being assessed. Patrolling can then be understood as a cyclic version of probabilistic search where the same location can be visited more than once. Considering the targets' behaviour can greatly enhance the effectiveness of the search strategy (Robin and Lacroix, 2016). For the particular search strategy of patrolling, the mathematical concept of game theory have been used in Amigoni et al. (2009) to model the target's decision making.

After a target has been detected, it needs to be tracked in the second phase of the mission (right branch of Figure 4). Trapped victims in a collapsed building might try to find their way out of the debris and in order to evacuate them and get them out of the danger zone, it is imperative not to lose the victims once they have been detected. Since there are multiple robots available in the fleet, these can engage in target localisation. At the same time, each robot can have one or more targets assigned,

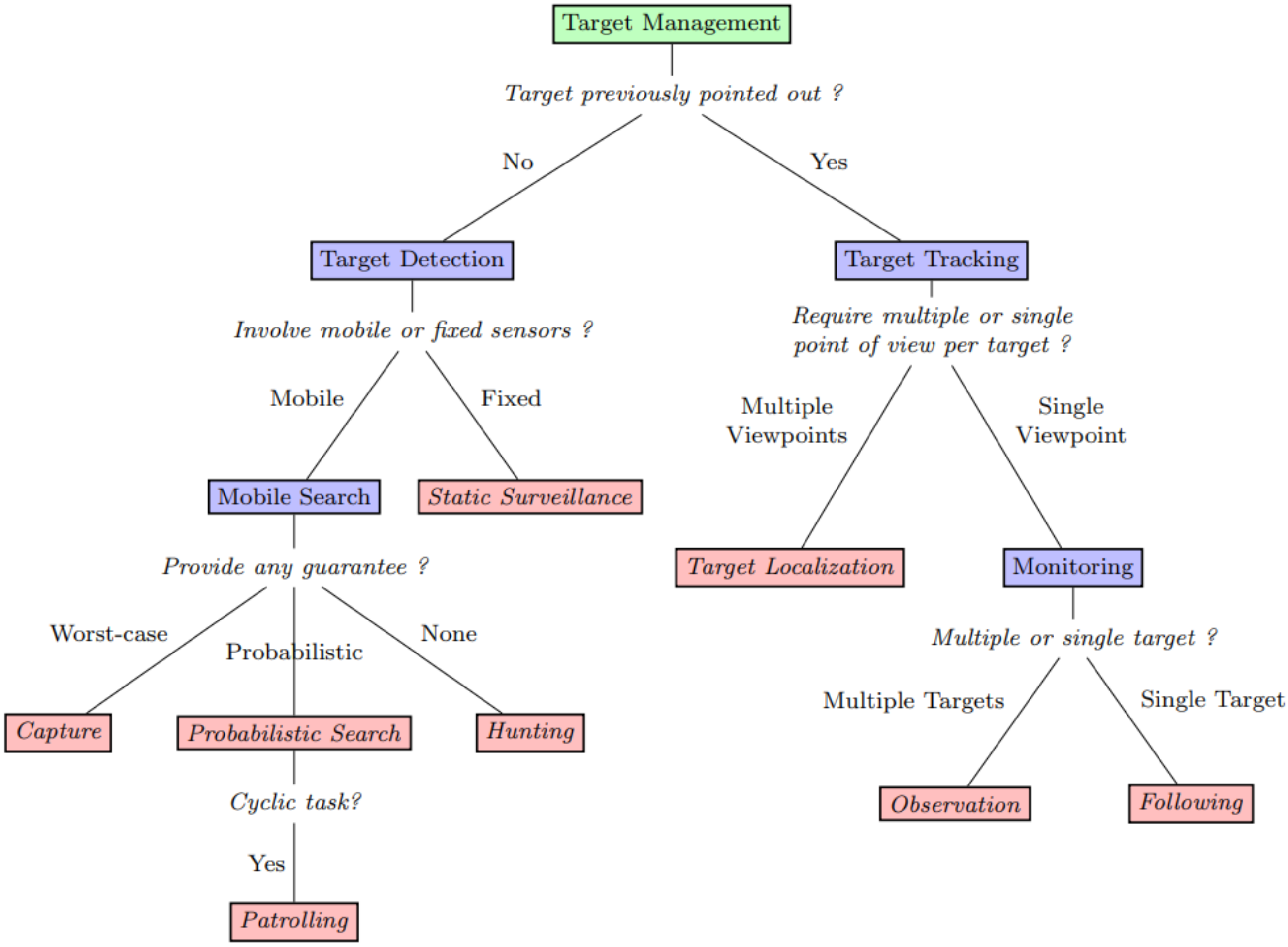

Figure 4: Levels of Risk from (Robin and Lacroix, 2016)

thus including observation and following tasks as can be seen in Figure 4 (Robin and Lacroix, 2016). In this case, an additional challenge arises for determining the most efficient target allocation for each robot. For the planning of following tasks, a behavioural model of the targets to be tracked has been used in Bandyopadhyay et al. (2009). Doing so can give an idea on how victims might take decisions and where they might move towards in order to get out of the disaster setting.

3.3 Key Take Aways

Indoor SaR environments are highly complex. The number of victims is unknown as well as their initial locations, which complicates the target management task riof a fleet of robots. The fleet must, after determining destinations to go to, assign these amongst each other in the optimal way and determine the most efficient trajectories to get to their targets. During all this, the environment is highly dynamic and therefore constantly changing.

In order to alleviate these tasks of SaR missions, an understanding of how the targets that are to be found and rescued is needed. Therefore, the next section focuses on how to model the behaviour of victims that attempt to escape from the disaster site.

4 Modelling Evacuation Scenarios

For an effective mission planning in the context of SaR missions, an understanding of the behaviour of trapped victims is imperative. This section first introduces the characteristics of multi-actor systems and suited modelling techniques. A focus is then set on the background of agent based modelling and of game theory for modelling decision taking in a multi-actor setting. In each section, a review is given about existing evacuation models while an overview of the reviewed models can be found in Table 3.

4.1 Multi-Actor Systems

An evacuation situation can be described as a multi-actor system. In a multi-actor system, there are multiple actors where an actor refers to a person or rather a trapped victim in the disaster scene. Each actor has certain capabilities to act and to influence the decisions taken by the other actors in the system. It is assumed that in general, no single actor is able to impose its preferred solution upon all other actors. They are all interdependent and there is some form of interaction needed between the actors (Hermans and Cunningham, 2018).

To illustrate using a hypothetical example, after being trapped together in a collapsed building, several actors will want to use the one single exit that is left in the room to get out of the building. Since only one actor at a time fits through this door and there is a fire expanding on the other side of the room, every actor will want to get through this door as fast as possible. The actors will therefore need to reach a decision together about the order of actors that through this door.

Multi-actor systems can be described on multiple levels. On more abstract, macro levels actors are considered to be embedded in a network that dictates the social relations between the actors. Here, institutional rules restrict the possible range of actions of the actors. This is a common view on actors for policy analysis but cannot explain how the system adapts to changes and disruptions, which is needed for understanding evacuation behaviour (Hermans and Cunningham, 2018) .

A lower level, micro perspective on agents is thus needed. A common way to explain actor behaviour is to use the conceptual dimensions of perceptions, values and resources. Perceptions relate to the way of how the actors think the world is operating. It can also be translated to 'neutral' beliefs, as opposed to 'normative' beliefs about what is right or wrong. Those 'normative' beliefs can be regarded as values about which states of the world are desirable. Thus, they reflect the internal motivation of the actors and are closely linked to an actor's perceptions. Finally, each actor has resources or means to realise their objective which again is based on their values and perceptions. (Hermans and Cunningham, 2018)

In a system where multiple actor are involved with different characteristic and preference, the overall behaviour of the system emerges from the interactions between these individual actors. Since these are too complex to understand using a mental model, a computational model is needed to understand what exactly happens during an evacuation scenario.

There are many different techniques for modelling evacuation situations. These can be divided into microscopic and macroscopic models, depending on the aim of the analysis (Bakar et al., 2017). Microscopic modelling techniques include social force models, lattice gas approaches and belief-desire-intention models using cellular automata or agent based models (ABM). Macroscopic models are for instance fluid dynamics models (Henderson, 1971). Other approaches are animal experiments or game theory. All of these have their drawbacks and advantages and for best results, Zheng et al. (2009) suggest further research into combining these techniques.

Macroscopic models have the major limitation that they cannot take into account the interactions amongst the actors, as they model the entire crowd as a whole (Bakar et al., 2017). During an emergency however, it cannot be assumed that a crowd of people will act as one group. Drury et al. (2009) for instance show that in evacuation situations, people form groups, such as with friends or colleagues with which they are trapped in the building, and are more likely to help members of their in-group than out-group members.

How these groups emerge depends on the individual characteristics of the actors and how they interact Braun et al. (2003). In order to understand these phenomena and how actors take these decisions, it is therefore imperative to model this process explicitly. Microscopic models are able to capture this as they model the interactions between actors and the overall pattern of the crowd emerges from these microscopic interactions.

4.2 Agent-Based Modelling

A common tool to implement microscopic models is Agent Based Modelling (Adam et al., 2017; Adam and Gaudou, 2016). An ABM is a computational tool for simulating geo-spatial systems, namely systems that are continuously changing in time and space. This dynamics is due to the microscopic interactions between individuals as well as between an individual and the environment. Thus, a global pattern emerges and the behaviour of the system can be analysed using computational experiments. In contrast to for instance cellular automata, more complex rules can be defined for the agents to interact with each other (Crooks and Heppenstall, 2012).

4.2.1 Background

In an ABM, the actors that are included in a simulation model are called agents. These agents are active which leads to them having the following features (Crooks and Heppenstall, 2012):

- Proactive and goal directed: The agents of a model have a goal that they need to achieve. This could be the maximising of a utility function and depends on their characteristics.
- Reactive and perceptive: The agents have knowledge about their environment based to which they can react.
- Bounded Rationality: The agents can make inductive decisions to achieve their goals.
- Interactive and communicative: The agents exchange information with other agents in the environment and interact with each other and the environment.
- Mobile: The agents can move through the environment during the simulation. They can also be fixed, depending on the aim of the simulation.
- Adaptive: The agents can learn based on their previous states.

- Autonomous: The agents are free to interact with other agents and the environment to process information and exchange it with other agents and to make independent decisions.

- Heterogeneous: The agents have individual characteristics, such as age or jobs. Grouping of similar agents can arise, which is then due to the interactions on a microscopic level.

The agents interact with the environment and with each other based on a set of pre-defined rules. These rules as well as the characteristics of the agents are derived from the modellers induced observations of the real world (Crooks and Heppenstall, 2012). The simulation environment in which agents are located is described as a neighbourhood through which they can move throughout the simulation. This neighbourhood can be a simple grid with cells that the agents can occupy or they can have specific geographical features. An agent can interact with other agents in the neighbourhood. In a Moore neighbourhood, an agent is allowed to interact with agents on all 8 surrounding cells, while in a Von Neumann neighbourhood, only the down, up, left and right cells can be reached (MESA Documentation, 2022).

ABMs can be constructed using general purpose programming languages (e.g. Python) with existing open sources modules (e.g. MESA (MESA Documentation, 2022)) or using specific programming languages and programming environments such as NetLogo (Tisue and Wilensky, 2004) or GAMA (GAMA, 2022).

Applications for ABMs include all sorts of complex systems, ranging from modelling and simulating the spread of diseases, market models to traffic jam formation. ABMs have also been used for modelling evacuation scenarios, such as in Hashimoto et al. (2022) and in Templeton et al. (2015).

Hashimoto et al. (2022) have used an ABM to model lost person behaviour in an outdoors, wilderness SaR mission, where a lost person is one that is disoriented and that is unable to identify its current situation. Six lost person behaviours are defined for the agents that are random walking (RW), route traveling (RT), direction traveling (DT), staying put (SP), view enhancing (VE) and backtracking (BT). The environment of the model is a 2 dimensional grid where each cell of the grid having specific geophysical and terrain characteristics. The lost person types are defined by a probability of the agent using a specific behaviour at each time step [RW, RT, DT, SP, VE, BT] where the sum add up to 1. At each time step, the agent's position is updated by a randomly selected strategy.

Trivedi and Rao (2018) have used an ABM to implement a social force model for modelling panic behaviour in an indoor evacuation scenario. The agents move based on three simple flocking rules, as initially proposed by Reynolds (1987). The first rule is cohesion referring to an agents trying to move towards the center or the crowd. The second rule is alignment where each agent seeks to align itself with the direction in which the crowd moves. The last rule is separation, where an agents moves away from another agent as soon as they get too close to each other. Panic is calculated based on four factors; the distance to the door, the velocity of neighbours moving towards the door, the number of neighbours that have a high degree of physical discomfort and the lag in velocity. Based on the flocking rule and the calculated panic, the positions of each agent are updated at each time step. An overview of their model is given in Figure 5.

While these applications of ABMs aim at implementing the emergence of a global behaviour based on the microscopic interactions between the actors, incorporating psychological and emotional factors

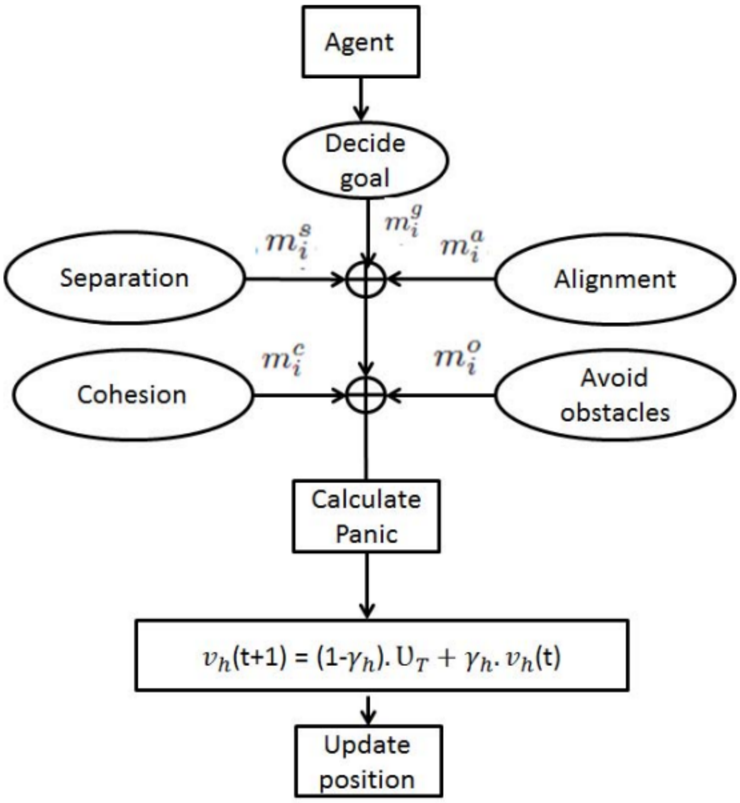

Figure 5: Agent based evacuationBM model from (Trivedi and Rao, 2018)

remains a challenge (Templeton et al., 2015). To illustrate, in Hashimoto et al. (2022), the agents choose their strategies randomly at each time step while in Templeton et al. (2015), the agents move based on flocking behaviour. According to Axelrod (1997), it is desirable to keep a model as simple as possible in order to be able to keep track of what parts of a model might be responsible for a particular result. In order to recreate human decision making more realistically, however cognitive and emotional characteristics of the actors should be included in a model (Adam and Gaudou, 2016).

4.2.2 Belief-Desire-Intention Framework for ABMs

The Belief-Desire-Intentio (BDI) framework reflects the research of Bratman (1987) into human practical reasoning and the planning theory of intentions.

Agents in the BDI framework reflect similar notions as actors in the multi-actor framework and are well suited for modelling multi-actor systems, in contrast of social force models or lattice gas approaches. BDI agents have the following features (Rao et al., 1995; Balke and Gilbert, 2014):

- They have beliefs about the state of the world, similarly to the notion of perceptions in multi-actor systems. These beliefs can change and new beliefs can be added to the belief set as the system changes. To give an example from a disaster scene, a belief could be about the speed of fire spreading.
- Desires can be compared to values and reflect the motivation of an actor, hence situations that the agent would like to happen. In an evacuation setting, this could be the desire to get to safety.

An 'activated' desire can be seen as a goal, namely a desire the agent is currently committed to. To illustrate, it might be desirable for an agent to get out of the disaster setting herself and at the same time be desirable that the neighbour gets out safe as well. Since there is only one exit, this cannot happen at the same time and only one of these desires can be 'activated' into a goal.

- Finally, intentions reflect what an agent has chosen to do. In order to achieve an intention, several plans are needed. To illustrate, when the actor has chosen to get out of the collapsed building, this intention is fulfilled by first getting ways from the fire, then getting to the exit and then to the other side of the street.

By using the BDI framework to model the ABM's agents, the process of making a plan and executing the latter can be considered specifically. This way, an ABM that models the interactions between the different agents does not only capture the emerging pattern from these intentions, but with the BDI framework also captures how these interactions come about. Hence, when using the BDI framework for ABMs, the inductive modelling process and the modeller's assumptions can be backed by a theory to describe how humans reason and plan.

The BDI framework has been used to model cooperation between agents in various contexts. Not an evacuation scenario but a useful example to illustrate the workings of a BDI model is the model of an artificial soccer game (Burkhard et al., 1997). Each agent, having a fixed role in the team, has a world module, a planning module, a sense, an act and skills module in Figure 6. By acting, the agent changes the world and hence its beliefs about the situation. The planning and skills module can be used by the agents to simulate consequences of their actions, for instance estimate the velocity and future position of the ball after kicking it or estimating own and teammates' positions around the ball. Positions are sensed using visual information. After new sensor information is available, the planning process is started and a goal (being a desire), such as passing the ball to a teammate, is selected by classifying the situation using a decision tree (Burkhard et al., 1997).

There have also been evacuation models constructed using the BDI framework. The BEN model (behaviour with emotions and norms) from (Bourgais et al., 2020) is a BDI model that includes emotions (personality, social relationships, emotional contagion) and norms (laws, obligations) to an agent's behaviour. The overall functioning of the BEN architecture can be seen in Figure 7. The model is implemented in the GAMA platform (GAMA, 2022) and is validated on a real-life evacuation scenario, called the Kiss Nightclub (BBC, 2013; Atiyeh, 2013).

The first submodule serves the agent to perceive the environment ('perceptionActivated' in Figure 7). Information is transformed into cognitive mental states and emotions. Perceptions are formed into beliefs and the belief set is updated. If an agent for instance perceives fire, its beliefs about there being fire are updated. If an agent observes another agent, social relations are created and emotional contagion about the fear of fire are executed.

Moreover, the model has a knowledge updating submodule ('managingKnowledgeActivated' in Figure 7). This updates the emotions as well as the knowledge bases based on the latest perceptions. To do so, new emotions, desires, obligations and social relations are added.

Additionally, there is the decision making module ('makeDecision' in Figure 7). The cognitive and normative engine determine whether a current intention and/or plan/norm is to be kept. Potentially

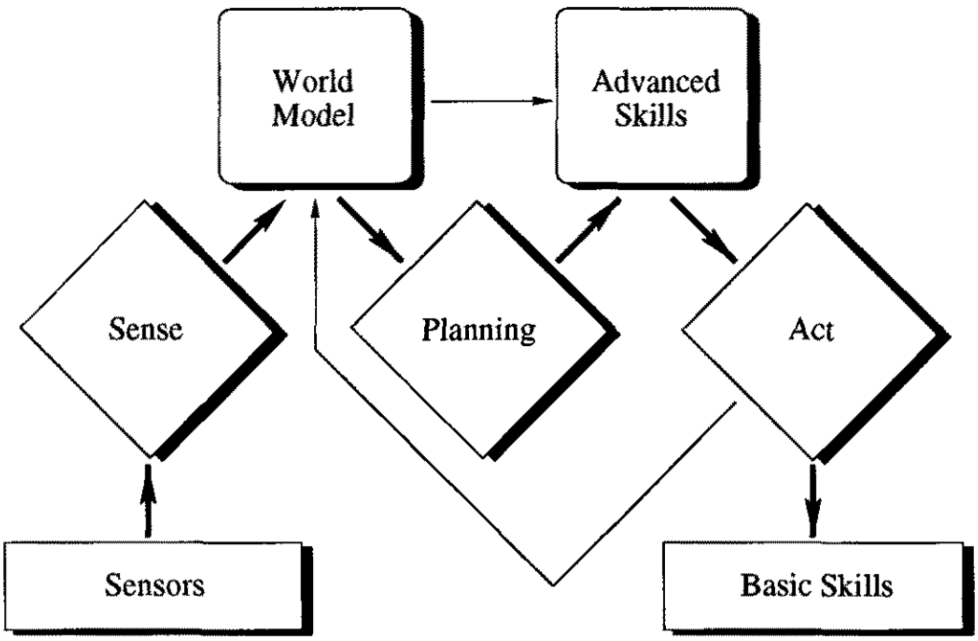

Figure 6: Architecture of a soccer agent from (Burkhard et al., 1997)

a new plan/norm is chosen based on a (new) selected intention (desire or obligation) (see Figure 8), based on a decision tree.

Finally, there is temporal dynamics component that degrades emotions and updates norms over time ('knowledgeDynamicsActivated' in Figure 7)

Another evacuation model using BDI is the IMPACT model from (Van der Wal et al., 2017), implemented in NetLogo. The model aims to extend previous evacuation models with socio-cultural, cognitive and emotional factors. Group decision making is also taken into account via emotional contagion. Each agent has 4 modules: Based on 'Input' form the environment, the modules 'Individual Characteristics' (in orange in Figure 9), 'People-People Interactions' (blue), 'People Environment Interactions' (green), all interact and lead to 'Decision-Making' (yellow). This results in 'Actions' that change the environment.

These 4 modules have different concepts (features, beliefs, desires and intentions) that dynamically interact as shown in Figure 9. To illustrate, the action move to exit' (which is a 'People Environment Interaction') is influenced by the familiarity of the environment and speed (both 'Individual Characteristics') and the intention and desire to evacuate (both 'Decision-Making'). Another example is the 'action help other' (which is a 'People-People Interaction') depends on 'fall' ('People Environment Interactions') and 'group membership' ('Decision-Making'), amongst other factors.

These are modelled using differential equations, where for each agent also the state of others are taken into account. To given an example, Equation 1 computes the desire to evacuate. The desire to evacuate ranges from maximum desire being 1, to minimum desire, being 0. In this equation, $d_e(t)$ denotes the desire to evacuate, c the compliance, a the amplifying evacuation factor. b_d the belief dangerous. $o_s(t)$ the observation staff instructions, and $o_a(t)$ the observation public announcements.

$$d_e(t)(t+\delta t) = d_e(t)(t) + \eta * ((c * (\max(\omega_a * b_d(t), \omega_a * fear(t), \omega_a * o_s(t), \omega_a * o_a c(t)))) - d_e(t)) * \delta t \quad (1)$$

```
begin
    if perceptionActivated then
        if creating_beliefs) then
            perceive(Environment);
            createBeliefs;
        end
        if emotional_contagion then
            perceive(OtherAgentsEmotions);
            emotionalContagion;
        end
        if creating_social_relation then
            perceive(OtherAgents);
            createSocialReltations;
        end
        if applying_sanctions then
            perceive(OtherNorms);
            applySanction;
        end
    end
    if managingKnowledgeActivated then
        if inference_rules then
            executeInferenceRules;
        end
        if laws then
            executeLaws;
        end
        if emotional_engine then
            manageEmotions;
        end
        if social_engine then
            manageSocialReltaions;
        end
    end
    if normative_engine then
        makeDecision(normative_engine);
    end
    if noDecisionMade then
        makeDecision(congnitive_engine);
    end
    executePlan;
    if knowledgeDynamicsActivated then
        if lifetime then
            degradeMentalState;
        end
        if emotionIntensity then
            degradeEmotions;
        end
        if normViolation then
            updateNormStatus;
        end
    end
end
```

Figure 7: Architecture of the BEN model from (Bourgais et al., 2020)

While in general, the BDI framework extends an ABM by incorporating the reasoning process for making individual plans, the decisions the agents take when interacting with other agents also need to be modelled in more detail. In Burkhard et al. (1997) and Bourgais et al. (2020), the final decision is taken based on a decision tree and it is not clear how the decisions are taken on a collective level. In Van der Wal et al. (2017), group decision making is included but is solely based on social contagion. It can be assumed that actors during an evacuation scenario also engage in some rational strategic reasoning processes to collectively make decisions.

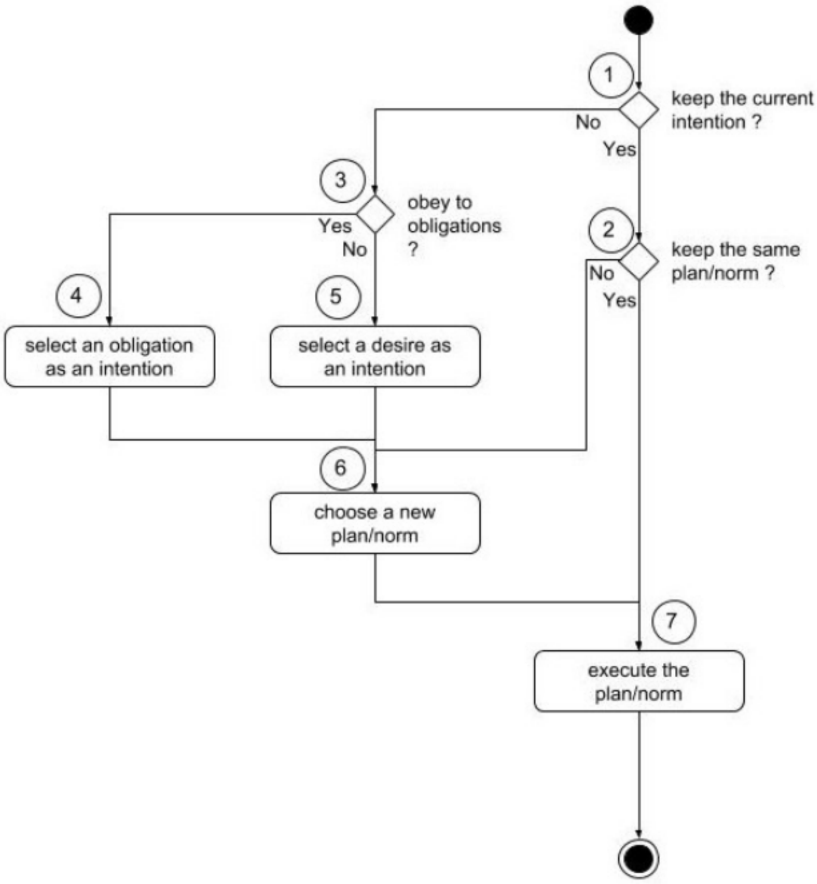

Figure 8: The decision making process of the BEN model from (Bourgais et al., 2020)

4.3 Game Theory

Game theory can be explained as a set of mathematical tools to explain the interactions between decision-makers (Osborne and Rubinstein, 1994). A game refers to the representation of different strategies to achieve different outcomes based on a given situation and the values that the actors included in the game, called players in the notation of game theory, associate to the game. Players include all those actors that are engaged in the decision making process. Each player is assumed to be of bounded rationality, namely they want to maximise a certain utility for which they have limited information to base their decisions on (Osborne and Rubinstein, 1994; Hermans and Cunningham, 2018).

Each player also has a set of moves or actions. The sequence of these actions refers to their strategies and can be based on the anticipation of the decisions of other players. The outcome of the game is the result of the combination of the strategies of all players. Each player prefers different outcomes and the value a player assigns to a particular outcome is called the payoff. The game is subject to rules which limits the set of possible moves and actions a player can make. In an evacuation scenario, the utility could be to get out of the emergency setting as fast as possible. To achieve this, they have several moves, such as cooperating with the other people at the nearest exit or forcing the way through. Each of these actions have different payoffs, depending on what they mean to the player

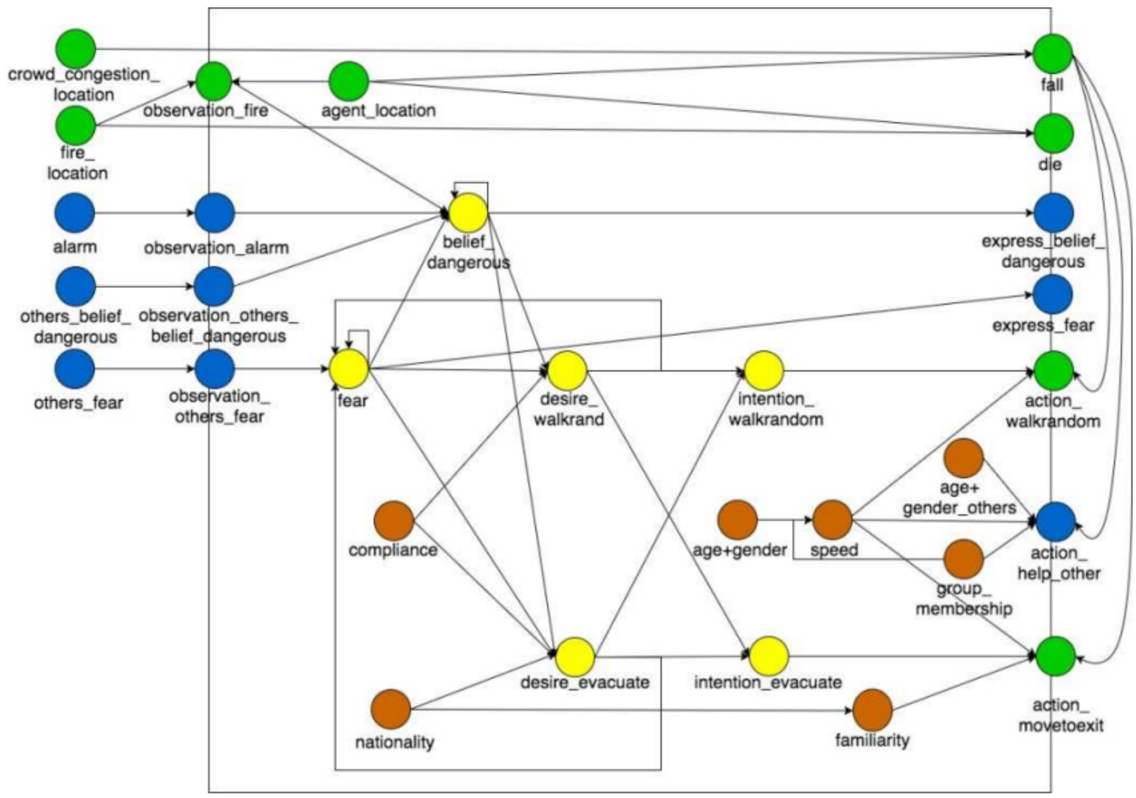

Figure 9: Relationship between modules of IMPACT model from (Van der Wal et al., 2017)

(Osborne and Rubinstein, 1994; Hermans and Cunningham, 2018).

A plethora of different types of games can be distinguished with different solution concepts. Which concept to use for the mathematical formulation of the problem depends on the use case (Osborne and Rubinstein, 1994). Most notably, there are cooperative and non cooperative games which will be explained more in detail in the following section. An overview of concepts can be found in Table 1 and solutions.

4.3.1 Cooperative Game Theory

Cooperative game theory analyses the creation of alliances, coalitions and groups that bring additional value for the individual players in these groups. In general, actors are assumed to be rational and take rational decisions, thus maximising the utility they expected to be resulting from the game. When considering cooperation, collective action is considered as well and hypothetical values resulting from creating coalitions is needed (Hermans et al., 2014; Wang et al., 2003).

The goal of cooperative theory is to determine which players should cooperate with which, which actions they jointly take and how much each actor should be willing to sacrifice for the the common interest of the coalition. In general, cooperative games can also be analysed using non cooperative game theory that could theoretically include all available strategies for strategic bargaining to enforce a cooperation (Osborne and Rubinstein, 1994).

A cooperative game is represented in characteristic function form, such as in Figure 10 from

(Hermans et al., 2014). Here, assumptions must be made about the value of the coalition for the players for instance when faced with a hostile reaction from the remaining players. The point is not to choose the most realistic value for each coalition but to have a relative quantification of the coalitions. To illustrate, in Figure 10, there are 4 players, namely players R, W, M and N. The grand coalition given by v(RWMN) includes all players and has a payoff of 81 units. The zero coalition $v(\emptyset)$ is per definition equal to 0 units. A coalition between R and N solely has a payoff of 69 units while cooperating together with W would result in a higher payoff of 100 units. This is can be argued that, depending on how these units are distributed amongst the members of the coalition, player R will prefer cooperating with W over the grand coalition, which it still prefers over cooperating with N.

$\nu\{\phi\} = 0$

$\nu\{R\} = 94$ $\quad$ $\nu\{W\} = 8$ $\quad$ $\nu\{M\} = 13$ $\quad$ $\nu\{N\} = 19$

$\nu\{RW\} = 100$ $\quad$ $\nu\{RM\} = 63$ $\quad$ $\nu\{RN\} = 69$ $\quad$ $\nu\{RM\} = 38$ $\quad$ $\nu\{WN\} = 44$ $\quad$ $\nu\{MN\} = 6$

$\nu\{WMN\} = 31$ $\quad$ $\nu\{RMN\} = 69$ $\quad$ $\nu\{RWN\} = 75$ $\quad$ $\nu\{RWM\} = 75$

$\nu\{RWMN\} = 81$

Figure 10: Characteristic function form of a 4 player game from (Hermans et al., 2014) where v(.) refers to the value of the indicated coalition to the members of the coalition indicated by a letter.

The values that each coalition constitutes for their members needs to be determined. For this, there are different solution concepts, there being the Core, the Shapley value and the Nucleolus.

Mathematically, a coalitional game as described above is given by a set N with n players and the characteristic function v that attributes a subset of players to a real number. Hence, given a coalition S of players, then the total expected payoff that all the members of S can expect is given by *v(S)*. The outcome of a game can be understood as the payoff vector $x = (x_1, x_2, ..., x_n)$. The core is then given by three conditions. First, individual rationality must be met: $x_i \geq v(i)$, which means that the payoff x_i player i gets from a coalition S should be at least what player i gets when not being a member of the coalition. Second, group rationality must be met: $\sum_{i=1}^{N} x_i \geq v(S)$, meaning that the sum of the payoffs x_i must at least meet value $v(S)$ of the coalition S. Finally, the coalition must be jointly efficient with $\sum_{i=1}^{N} x_i = v(N)$. where $v(N)$ denotes the grand coalition of which all players are member of Hence, the sum of all the payoffs that the players receive needs to add up to the value of the grand coalition.

The Core value aims at meeting the needs of the individual as well as of the group. It refers to the 'Best Alternative to a Negotiated Agreement', meaning that a player cannot be assigned less utility than they would have gotten in a different, smaller coalition. The Core can thus be understood as the intersection of the three linear inequalities above and hence it is not always assured that a game has indeed a core (Shubik, 1981; Wang et al., 2003).

The second solution concept is the Nucleolus value. The Nucleolus aims at minimizing the maximal excess. In other words it aims at minimizing dissatisfaction and thus making the most unhappy player as little unhappy as possible (Wang et al., 2003; Shubik, 1981).

When defining $x(S) = \sum x_i$, the excess e can be given by $e(S,x) = v(S) - x(S)$. Then, the nucleolus is found by Equation 2.

$$\min e(S,x) \quad \text{s.t.} \quad x(S) + e(S,x) \geq v(S) \tag{2}$$

The third solution concept is the Shapley Value which can be described as the 'fair reward' to the players, based on what they bring to the negotiation table. Each player gets a weighted average of what the player contributes to the coalition (Wang et al., 2003; Shubik, 1981).

The Shapley value is computed according to Equation 3, where N is the set of players in the game.

$$x_i = \sum_{S \subseteq N \setminus \{i\}} \frac{(S-1)!(n-S)!}{n!} [v(S) - v(S \cup \{i\})] \tag{3}$$

Figure 11 shows the solution of a three player cooperative game from (Wang et al., 2003), where all players need to share a water resource. Each edge of the triangle represents the single player coalition of each player (City 1, City 2 and a player called IWA). From the values in brackets it can be seen that the payoff for the players that are not in the coalition is zero. When moving along the edges of the ternary plot, the value for the 2 player coalitions can be estimated, while the value for the player opposite to the edge is still zero. Inside of the triangle are the possible values for the grand coalition which includes all players. The green area shows the core were all the conditions for coalition efficiency, individual rationality and group rationality are met. The Shapley value and the Nucleolus value are usually located within this region (Hermans et al., 2014).

While game theory in general has been used for evacuation models, cooperative game theory has not been as widely used. One application has been of Collins and Frydenlund (2016) who use cooperative game theory to study the strategic formation of groups in migration flows of refugees. For this, the authors use the concept of the Core as solution concept to incorporate into an ABM of an evacuation scenario. Each agent's utility function has two parts that are given different importance, the first representing speed of reaching the desired destination and the second the protection stemming from belonging to a group in Equation 4. $s(a)$ denotes the maximum speed of agent a and $G(a)$ refers to the group to which agent a currently belongs to. The total number of agents is given by N and λ is a weighting factor (Collins and Frydenlund, 2016). the chosen group of agent a is calculated as the following where $|.|$ denotes cardinality.

$$V(a) = \lambda \min_{x \in G(a)} s(a) + (1-\lambda)(|G(a)| - 0.5)/N \tag{4}$$

This results in the three strategies of (1) kicking members out that are too slow, (2) of leaving a group and switch to a faster group and (3) of supergroup formation, where people end up clustering into one or two huge groups. At each time steps, all agents check if they can employ a strategy to achieve a higher payoff. The authors run their simulations with NetLogo but do not find the Core of the game (i.e. a distribution in subgroups, where each agent gets the highest possible payoff compared to all other sub-group formations), since this would be too computationally intensive with the 153 agents they consider, as each subgroup would need to be evaluated for each time step. The authors instead only consider, at each time step, one stochastically generated subgroup for each agent based on

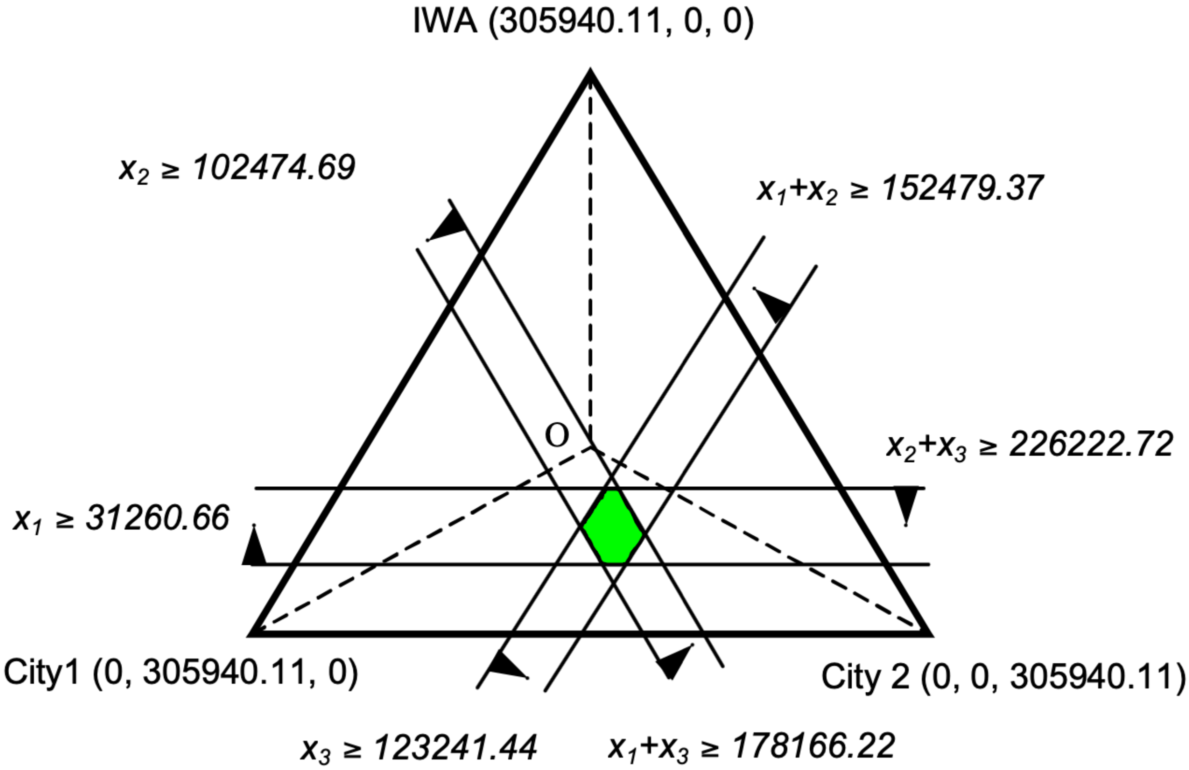

Figure 11: Ternary plot of a three player cooperative game for water allocation according to Wang et al. (2003)

the agents in its neibhourhood(Collins and Frydenlund, 2016).

4.3.2 Non-cooperative Game Theory

In contrast to cooperative game theory, non cooperative game theory only considers one player's individual actions and its individual utility. Different strategic interactions amongst the players can be analysed using non cooperative game theory, these being the Nash equilibrium, the Pareto optimum and the Hick's optimum.

Simultaneous games are usually given in normal form, such as in Figure 12 from (Gibbons, 1997) and are designed for competitive games with no cooperation. It is based on the assumption of complete information, namely both players know their respective payoffs. However, both players have no knowledge about the strategy chosen by the other player. The payoffs for each move can be seen in each matrix cell. In the game in Figure 12 a rational player 1, knowing that player 2 is rational as well, will assume that player 2 will never choose strategy 'Right', since 'Right' is dominated by 'Middle'. Whether player 1 opts for 'Down' or not, player 2 is always better off choosing 'Middle' rather than 'Right'. Hence, as player 2 will choose either 'Left' or 'Middle', player 1 will always be better off going for 'Up' as here its payoff is always greater than when going 'Down'. Since player 2 is rational as well as can do the same reasoning, it knows that player 2 goes 'Up' and therefore chooses 'Middle'. Hence, the solution for this game is (Up, Middle) for players 1 and 2 respectively Gibbons (1997).

		Player 2		
		Left	Middle	Right
Player 1	Up	1, 0	1, 2	0, 1
	Down	0, 3	0, 1	2, 0

Figure 12: Non cooperative simultaneous game between two players in normal form from (Gibbons, 1997)

This reasoning process can be formally given using the solution concept of the Nash equilibrium. The payoff function of a player i is given by $P_i(st_i, ..., st_n)$. Then, the equilibrium is the set of strategies given by $(st_i^*, ..., st_n^*)$, for which Equation 5 is satisfied for all $i = 1, 2, ...n$. Thus, Shubik (1981) gives:

$$P_i(st_i^*, ..., st_n^*) = \max_{st_i \in S_i} P_i(st_i, ..., st_n) \tag{5}$$

The Nash equilibrium is the most commonly used solution concept in non cooperative game theory. It assumes no trust and no cooperation between the players and it can result in social dilemmas and the so called 'Tragedy of the Commons', where due to the focus on individual payoffs, the collective use of a resources is not efficient. An example of this is the so-called Prisoner's dilemma shown in Figure 13. The upper left cell shows the prison sentence for both players if they both cooperate. The lower left and upper right show the payoff they get if one of them cooperates and the other defects (betrays). The lower right shows the payoffs they receive when both defecting. Thus, it can be seen that both players will always get a higher payoff if they defect, no matter what the other player does. If player 1 cooperate, player 2 should defect. If player 2 defects, player 2 should do so as well. Mutual cooperation would have resulted in an overall better payoff but would have been irrational from an individual perspective. This is thus a game, where the Nash equilibrium is not Pareto efficient: Pareto efficiency, a second solution concept for non cooperative game theory, is achieved when no player can further improve its pay-off without reducing the pay-off of another player. For this it is assumed that all players want to avoid a lose-lose situation and that it is not possible to take from one player to give to another (Osborne and Rubinstein, 1994; Shubik, 1981; Hermans and Cunningham, 2018).

Next to the Pareto Optimum and the Nash Equilibrium, the Hicks Optimum is a third solution concept for non cooperative game theory. It refers to the maximum combined payoff, where the players need to be willing to redistribute and the payoff is transferable. It is assumed that the payoff that players attribute to their desired outcome during evacuation scenarios is not transferable. Therefore, this solution concept will not be considered (Hermans and Cunningham, 2018).

Games with complete information as the two games above can be distinguished from those with incomplete information. While so far both players were assumed to be aware of the other's payoff, now

		Player 2	
		L_2	R_2
Player 1	L_1	1, 1	5, 0
	R_1	0, 5	4, 4

Figure 13: Prisoner's Dilemma from (Gibbons, 1997)

there will be probabilities introduced and the games treated as a Bayesian game. An example is given in Figure 14, where two players are on a date and need to make a choice regarding what they will order. Chris has the choice between either Steak or Chicken, based on Pat's choice of either red or White wine. In this game, they do not know the utility of the other player and hence do not know which strategy they will choose. Therefore Chris will choose Steak if t_c exceeds a critical value c, while Pat chooses white wine if t_p exceeds a critical value p. Hence, the probability with which Chris chooses Steak is $\frac{x-c}{x}$ and for Pat to choose white wine is $\frac{x-p}{x}$. with x denoting their expected payoff. Based on these probabilities, a Bayesian Nash equilibrium can then be determined. However, equilibria can potentially arise that include non credible beliefs and result in strategies that rational players would not carry out since it would be in their best interest (Gibbons, 1997).

		Pat	
		Red	White
Chris	Steak	$2 + t_c$, 1	0, 0
	Chicken	0, 0	1, $2 + t_p$

Figure 14: Bayesian game from (Gibbons, 1997)

Finally, there are evolutionary games which are often explained with the example of the two player game of the 'Hawk & Dove' competition. They need to share a resource and based on whether a hawk meets another hawk or a dove and a dove meets another dove or a hawk, receive a different payoff. This payoff depends on the probability of meeting a dove and a hawk. This probability again depends on the amount of doves and hawks in the population of birds which is based on the previous outcomes of the game (Osborne and Rubinstein, 1994).

For evacuation scenarios, there are several models using non cooperative game theory. Wang et al. (2014) and Bouzat and Kuperman (2014) both consider an indoor evacuation scenario in which

Table 1: Different concepts in game theory

Game Theoretic Concept		Form	Assumptions	Limitations
Cooperative Games		Characteristic function form	Collective Behaviour	No bargaining
Non Cooperative Games	Bayesian Games	Normal Form	Incomplete information	Non credible beliefs
	Simultaneous Games	Normal Form	Complete information	Competitive environments
	Evolutionary Games	Normal Form	Strategy Changes	Multiple rounds

Table 2: Different methods to games

Game Theoretic Solutions	Explanation	Assumptions
Nash	No player wants to change their strategy unillaterally	Correct beliefs about other players
Pareto	No increase in payoff without descreasing other player's payoff	Players want to avoid a lose-lose situation
Hicks	maximum combined payoff	Transferable utility
Core	Best Alternative to a Negotiated Agreement	Transferable utility
Nucleolus	Minimizing dissatisfaction	Members of coalitions are not content with excess of coalition
Shapley	Fair reward, based on what players bring to coalition	Contribution to coalition is unequal

a two player game determines who can use the exit. They do so based on the rules similar to the Prisoner's Dilemma and consider the behaviours of 'Cooperator' and 'Defector'. Ibrahim et al. (2019) take this a step further and use a social force model for simulating the evacuation process of a crowd. The interaction of the actors in the crowd is modelled with game theory, where agents play against conflicting neighbours with the objective to reduce evacuation time and thereby increasing their payoff.

The estimated evacuation time of an agent's neighbour is given by $T_i(i_c) = \frac{T_i+\sum_{i_c=1}^{N_{ic}} T_{ic}}{1+N_{ic}}$ with N_{ic} denoting the number of neighbors i_c of agent i. The change in utility that a winner in the conflict gets and the losers loose is then define as $\delta u(T_i(i_c))$. The authors define four different strategies (cooperator, defector, evaluator and retaliate) that each receive a different payoff and introduce a conflict cost t_d that applies to actors that do not cooperate. It represents the lost time due to for instance pushing each other. The different strategies of the agents are updated simultaneously at each time step, based on the agents behaviour. There are 4 fixed types of behaviours, risk-averse (maximising the minimum available payoff), risk-seeking (maximax, i.e. maximising the maximum possible result), risk-neutral (minimax, i.e. earning regret when failing to choose best strategy) and best-response under certainty. The latter represents the behaviour to adapt under conditions, where agents are able to observe other agents' strategies in previous time steps (choosing the strategy that is at least as good as in previous time step). Figure 15 shows how the winners of each conflict in the crowd is computed. At each time step, the winners then get to move to their desired position at their preferred speed which is based on the total egress time and the safe egress time (Ibrahim et al., 2019).

Lo et al. (2006) use non cooperative game theory to explain how agents choose one out of multiple possible exits to leave a building. A two player game is first considered between the crowd and a 'virtual entity' representing the congestion of the exists. The crowd entity chooses an exit with the objective to minimise the exit time and the virtual entity represents congestion of the exists and tries to guess which exist the crowd will choose and blocks it. The result of this step is a Nash equilibrium of exit choices with probabilities.

The total evacuation time and hence the payoff is equal to a_ij under scenario (α_i, β_j), where β_j means that a capacity restriction is imposed on exit j and α_i mean that all players choose exit i. The value of a_ij then depends on the width of exit i as well as on the crowd density at exit i and the strategy β_j (Lo et al., 2006).

In the second step, each individual evacuee's decision needs to be determined, where each agent's distance to an exit i is used to adjust the probability of choosing it. This results then in the final probability exit choice matrix, based on congestion of the exit as well as on the distance of the agent to the exit. The model of Lo et al. (2006) thus does not use game theory to model the interactions between the individuals of a crowd, compared to Ibrahim et al. (2019) or Collins and Frydenlund (2016).

In (Wang et al., 2014), (Bouzat and Kuperman, 2014), (Ibrahim et al., 2019) and (Lo et al., 2006), the used utility functions are mostly based on reducing evacuation time to achieve maximum payoff. However, agents might also take other aspects into account, depending on their emotional state, their beliefs and desires. Hence game theory on its own is limited to realistically model the behaviour and the decision making of trapped victims in an indoor evacuation scenario.

Algorithm 1 Algorithm to decide the winner of the conflicts for the proposed automated spatial evacuation model

Identify strategy of current agent as defector or cooperator
Identify total number of defectors, number of large and equal defectors, and cooperators available in the neighbourhood of the current agent
Case based on number of defectors, large and equal defectors and cooperators
if number of defectors $>$ one and number of cooperators $\geq$ zero **then**
  if number of large defector = one **then**
    The large defector will be able to move while the rest of the defector(s) and all the cooperators would remain at the same location
    Payoff for the large defector $\leftarrow \Delta u(T_{i(i_c)}) - t_d$
    Payoff for defectors $\leftarrow -\Delta u(T_{i(i_c)}) - t_d$
    Payoff for cooperators $\leftarrow -\Delta u(T_{i(i_c)})$
  else if number of large defectors $>$ one **then**
    One of the large defectors will be able to move while the rest of the defector(s) and all the cooperators would remain at the same location
    Payoff for large defectors $\leftarrow \frac{\Delta u(T_{i(i_c)})}{L_{n_{def}}} - t_d$
    Payoff for defectors $\leftarrow -\Delta u(T_{i(i_c)}) - t_d$
    Payoff for cooperators $\leftarrow -\Delta u(T_{i(i_c)})$
  else if number of large defector $=$ zero **then**
    One of the defectors will be able to move while the rest of the defector(s) and all the cooperators would remain at the same location
    Payoff for defectors $\leftarrow \frac{\Delta u(T_{i(i_c)})}{n_{def}} - t_d$
    Payoff for cooperators $\leftarrow -\Delta u(T_{i(i_c)})$
  end if
else if number of defector $=$ one and number of cooperators $\geq$ one **then**
  The single defector will be able to move while all the cooperators will remain at the same location
  Payoff for defectors $\leftarrow \Delta u(T_{i(i_c)})$
  Payoff for cooperators $\leftarrow -\Delta u(T_{i(i_c)})$
else if number of defector $=$ zero and number of cooperators $>$ one **then**
  No winner and loser, the payoff is set equal to all cooperators as the conflicting agents will move together with the crowd based on the social force model
  Payoff for cooperators $\leftarrow \frac{\Delta u(T_{i(i_c)})}{n_{coop}}$
end if

Figure 15: Algorithm of Ibrahim et al. (2019) to decide on winner of conflict

Table 3: Reviewed models that use the concepts of ABMs, BDI, and game theory

Models	Framework	Application
Hashimoto et al. (2022)	ABM	Lost person behaviour
Trivedi and Rao (2018)	ABM, social force model	Panic for indoor evacuation
Bourgais et al. (2020)	BDI, ABM	Behavior, emotions and norms for indoor evacuation
Wal et al. (2017)	BDI, ABM	socio-cultural, cognitive and emotional factors for indoor evacuation
Collins and Frydenlund (2016)	Cooperative game theory, ABM	Formation of groups in migration flow
Ibrahim et al. (2019)	Evolutionary game theory, social force model	Game with conflicting neighbours for Indoor evacuation
Lo et al. (2006)	Non cooperative game theory, egress model	2 player game for exit choice in Indoor evacution

5 Indoor Evacuation Model: Game Theory and BDI

The utilization of search and rescue (SaR) robots in emergency response operations has proven to be instrumental in alleviating the burden on first responders. However, while significant research has focused on enhancing the technological aspects of these robots, the human element and the potential impact of their presence on victims' behavior have been largely overlooked.

The development of a behavioral model for trapped victims can assist in the mission planning of SaR operations. The review of existing literature shows that various tools are available for modeling human decision making. However, it is evident that these tools have limitations, such that further research is needed to incorporate more elements that accurately reflect human decision-making processes in a simulation model.

Moreover, it is crucial to note that no existing evacuation model currently incorporates SaR robots. As a result, none of the existing models can simulate the impact of these robots on human behavior during evacuations. The development of such a model would enable a comprehensive examination of how SaR robots can be effectively employed to assist in rescuing victims from emergency settings.

To address this research gap, a combination of tools such as Agent-Based Modeling, the Belief-Desire-Intention (BDI) framework, and game theory concepts emerges as a promising approach. By integrating these methodologies, it becomes possible to capture the cognitive and emotional reasoning processes of individuals, as well as to explain both individual and collective rationality in joint decision making during indoor evacuation scenarios.

Thus, in the remainder of this report, a combined model is built, the GT-BDI (game theory - BDI) model. This model is implemented in NetLogo and based and validated on prior research of Van der Wal et al. (2017) and Ibrahim et al. (2019). The specific use case of the model will be an indoor evacuation scenario. Furthermore, more research is done into human robot interaction and how trust affects this relation. These aspects are then implemented in the GT-BDI model and used to estimate the affect of the presence of SaR robots on human behavior.

6 Preliminary Conclusion

This report reviews the literature on SaR missions for fleets of robots that need to search for victims. In section 1, the societal relevance for this endeavour is stated. Disasters represent disruptions to the population to which they occur and they infer huge costs for the victims. Due to their very nature, disasters cannot be prevented and therefore, measures must be taken to reduce their disruptive character. In section 3, disaster management is introduced and the challenges that go alongside with the related activities are explained. Of these activities to respond to disasters are SaR missions. These need to be conducted in hostile environments that pose a life threatening risk to the first responders and rescue workers. Hence, the deployment of a fleet of robots is a promising solution to decrease risks where possible. Robots face their very own challenges when conducting a SaR mission. Their sensory capabilities can be impeded by the environment and the task of locating an tracking trapped victims is challenging. A model of how the victims behave can give insight into the location of the latter and alleviate the SaR mission. Thus, section 4 gives an overview of possible methods to create such a model. These range from ABM on its own, over the BDI framework to augment ABM models with cognitive and emotional features to game theory for individual and collective decision making. Game theory includes cooperative and non cooperative game theory, where cooperative game theory focuses on explaining how groups form in a crowd while non cooperative game theory focuses on how individuals maximise their own benefit. Finally, section 5 concludes that several of these tools lend themselves well to be combined into one model aiming at recreating human decision making as realistic as possible. Consequently, a model is proposed, based on non cooperative game theory integrated with a BDI model. This model is to be compared to an existing benchmark that is identified in the literature review of this report. To put it in a nutshell, the proposed model aims to give insight into how a crowd of agents in an indoor evacuation scenario takes decisions to provide a basis for efficient SaR mission planning and disaster management.

Part II

Thesis Paper

Mathematical modelling of emergency evacuation in the presence of search and rescue robots: A combined game theoretic and BDI-based approach

Laura Wilmes
TU Delft
Delft, The Netherlands
l.wilmes@student.tudelft.nl

***Abstract*—The impact of disasters on the affected population is catastrophic. Proper disaster management practices are needed to reduce their societal damage. This includes Search and Rescue (SaR) missions, which pertain measures to find potentially trapped victims. This task can be alleviated by the support of a fleet of SaR robots. This fleet is deployed to locate trapped victims and to report back their position to the emergency responders and potentially to follow them to track of their potential movements. Locating trapped victims is challenging, as the number of these people, their initial position and potential displacements may be unknown. A behavioral model of the victims can give insight on how they take decisions and act during an evacuation situation. Several techniques are used in the state of the art. This study proposes an evacuation model that integrates game theory into the belief-desire-intention framework. The model is validated with a benchmark from the state of the art. It is found that the model is able to produce realistic evacuation times. This depends on the distribution of the game theoretic strategies in the population. SaR robots are then added to the validated model. It is found that their presence reduces the evacuation time, depending on several parameters influencing trust of the victims in the robots. Thus, this research contributes to the field of research SaR operations by providing insight into the behaviour of the trapped victims in the presence of rescue robot.**

***Index Terms*—Evacuation, human behaviour, search and rescue robots, human-robot-interaction, game theory, BDI framework**

I. Introduction

Search and rescue (SaR) missions are performed very early as part of disaster response measures: Rescue workers need to secure the site of the disaster, locate victims, and rescue them from the potential risks. The decisive factor for the success of SaR missions is often the speed with which rescue workers are at place and can conduct SaR missions [1]. With technological advancements in various fields such as in robotics, sensorics, and autonomy, the field of SaR robotics has emerged. SaR robots can alleviate the task of rescue workers and support them in both finding and potentially saving the located victims from the disaster scene. Robots prove themselves helpful to assist in these tasks for various reasons. To name only a few, robots are expendable, they can participate in tasks that are hazardous for human rescue workers, and finally, depending on the extent of their autonomy, can take decisions at a much higher speed [1]. Disaster scenarios are highly complex. The environment is dynamic and people interact with each other in order to get themselves to safe areas. The behaviour of trapped victims can further increase the tragedy of disasters. A recent example is a soccer game in Indonesia, where around 125 people died due to stampedes, which resulted from people trying to evacuate from the soccer stadium [2]. Understanding how humans interact in a multi-actor setting can be a decisive factor for efficiently planning a SaR mission [3], with regard to the effective deployment of a fleet of robots. To illustrate, an event organizer could use the model to evaluate how people would move in their venue and how or where the deployment of SaR robots could benefit a speedy evacuation.

Different people have different intentions during a disaster, based on their individual goals. Some people might be willing to cooperate with others, while others will focus only on getting themselves out of an emergency setting [4]. Modelling and simulating human decision making is therefore a first step in order to be able to ultimately predict or at least estimate how people behave during an evacuation. As such, these predictions have the potential to further increase the speed and success of SaR mission.

This paper is structured as follows. First, the research questions to be answered and the contribution of this study are mentioned in Section II. Then, some background about modelling evacuation behaviour and about SaR robots is given in Section III. Section IV explains the methods that are used to answer the research questions. The case study that has been performed in this research, along with the constructed model and its results, and a discussion of these results and the limitations of the model are given in Section V. Finally, Section VI recapitulates the findings of the previous sections and proposes topics for future research

II. Contributions

This study aims at combining game theory (GT) with the Belief-Desire-Intention (BDI) framework to construct a validated evacuation model. Further, evacuation robots are added to the model in order to evaluate how their presence can influence the evacuation process. Thus, the research questions to be answered are the following:

RQ1: How can the BDI framework be adapted and integrated with game theory concepts to effectively capture the dynamics of human decision making during an indoor evacuation scenario?

RQ2: How can the combined BDI-game theory model be validated and evaluated to assess its effectiveness in accurately simulating and predicting human behavior during an indoor evacuation scenario?

RQ3: What are the factors that influence human interaction with SaR robots during an emergency evacuation?

RQ4: How does the introduction of SaR robots affect the overall evacuation time and evacuation success rate in indoor scenarios?

Thus, this study contributes to the state of the art by addressing the above four research questions, which have been formulated such that their answers fill in some of the knowledge gaps in modelling human behaviour during indoors evacuation settings, in the presence of evacuation robots. The main contributions of this paper are in particular the following:

- While there are existing, validated, and verified models of indoor evacuation scenarios, these only use separate frameworks for modelling human decision making in multi-actor settings. Integrating game theoretic concepts with the BDI framework for modelling an indoor evacuation, allows to combine the best of these two worlds. BDI models, on the one hand, are able to capture the cognitive processes of human decision making but do not necessarily capture the strategic decisions humans might take when confronted with having to make trade-offs regarding their own safety. GT, on the other hand, does capture these strategic considerations, but describes all interactions between humans as making trade-offs and maximising one's own payoff. This lacks all other dimensions of human interaction, which BDI does capture. Combining both approaches into one model enables a more realistic representation of human strategic decision making and and is a novel way of modelling human behavior during indoor evacuations.

- With including evacuation robots in the model, the effect of the presence of rescue robots onto the behaviour of the trapped victims can be analysed. So far, no indoor evacuation model includes a model of robots and of human robot interaction. In addition, while a lot of research is being conducted into trust of humans in automation and in robots, no implementation of a model of trust in an evacuation model was found when reviewing the state of the art. This implementation allows to evaluate how trust of the evacuees in the robots influences the resulting evacuation time. Simulating the influence of robots on decision-making of humans during indoor evacuations can help to efficiently plan and schedule the deployment of a fleet of SaR robots before the actual mission.

III. Background

In order to set the context of this research, this section covers the background of the most important elements of this study. As the aim of this research is to construct a validated evacuation model that captures reality as close as possible, this section first provides a glance about the state of the art of evacuation modelling and concludes that there are still some knowledge gaps in the state of the art. This is what answering the first research question aims to address, namely how to improve modelling human decision making in evacuation settings. Then, as this research also aims at introducing robots in the model, that assist the evacuating humans in escaping from the disaster scene, this section gives a brief overview of different evacuation robotics. Finally, as trust is an important concept in human robot interaction, this section introduces some important notions that describe the dynamics of trust in robots over time, that allow for answering the third research question about modelling evacuation robots and evaluating the influence of their presence.

A. *Evacuation Modelling*

In multi-actor systems, where there are multiple actor involved with different characteristics, the overall behaviour of the system emerges from the interactions of these individual actors. An evacuation scenario can be described as a multi-actor systems. The trapped victims all behave differently and from their interactions, a global behaviour can be derived. This emerging pattern is too complex to be understood with a mental model. Therefore, computational simulation models are often needed to grasp what is happening during an evacuation scenario.

There are many different techniques for modelling multi-actor systems, such as evacuation situations. These can be divided into microscopic and macroscopic models, depending on the aim of the analysis [5]. Microscopic modelling techniques include social force models, lattice gas approaches, and belief-desire-intention models using cellular automata or agent based models (ABM). Macroscopic models are for instance fluid dynamics models [6]. Another mathematical approach is GT. All of these have their drawbacks and advantages and for best results, [7] suggest further research into combining these techniques.

B. Evacuation Robots

The environments, in which SaR missions are conducted are often very complex. Indoors disaster scenes are often very cluttered. In the case of a collapsing building, there is a lot of rubble and debris. Therefore, SaR robots can assist rescue workers in the task of SaR missions. While there are many ways, in which robots can be used for SaR, in this study, they figures as evacuation robots. This means, that they assist the victims trapped in a disaster setting to evacuate from this building and guide the evacuees out of the danger zone. However, there are many difficulties in this task: To name a few, there is often an unknown number of victims is trapped in the building that need to be evacuated. Thus, the first step for the robots is often, to locate victims to be evacuated. While the victims are mostly considered to be stationary, they might still be locally moving when trying to get out of the disaster scene and to find their way out of the debris. This further complicates the mission planning for the robots [8]–[10].

Once having located the victims to be evacuated, it is thus imperative not to lose the victims once they have been detected [3]. In this study, the victims do not need to be detected. It is assumed that the evacuation robots have successfully performed the localisation task. At the same time, each robot can have one or more targets assigned for the observation and following tasks [3]. In this case, an additional challenge arises for determining the most efficient target allocation for each robot. For the planning of following tasks, a behavioural model of the targets to be tracked has been used in [11]. Doing so can give an idea on how victims might take decisions and where they might move towards in order to get out of the disaster setting. In this study, to each evacuation robot, victims are allocated to the particular robot that is in their field of view.

C. Trust in Robots

To determine to what extent these robots are helpful to speed up the evacuation process, the interaction of the evacuees with the evacuation robots needs to be evaluated. On the one hand, humans have a tendency to trust robots and systems less, when they do not understand them [12]. The more autonomous the robots appear to behave, the less humans might trust them, as they lack the transparency and explainability of the robots. On the other hand, however, research shows that especially in emergency situations, people tend to overtrust robots, even if they do not function correctly. In an evacuation situation, an example of a faulty robots could be one, that does take the lengthier path to the next exit. This overtrust can thus have severe consequences as the robots might potentially guide the evacuees to greater danger [12], [13].

[12] define trust as a "multidimensional psychological attitude". This attitude of humans (trustors) is based on their beliefs and expectations of a trustee's (robot) trustworthiness. This, in turn, depends on the humans' experience with this trustee in uncertain and risky situations. Thus, trust is dynamic over time with the phases of trust formation (trustor's decision to trust, depending on the predictability of the behaviour of the system, trust then potentially increasing over time when automation is reliable), trust dissolution (trustor's decision to lower trust after trust violation), and trust restoration (trust stops decreasing and is restoring).

With continued systems faults, trust decreases fast but then at some point begins recovering even if continuing faults. [14] make the distinction between acute failures (transient; e.g., repairable maintenance related failure), which make trust decline and recover, and chronic failures (e.g., software bug), which make trust decline until the humans have understood the faults and learnt how to handle them. First-order differential equations seem to capture the change of trust over time. The largest effect will be right away, while residual effects remain over time.

Also, there seem to be differential effects, where small faults have a small effect on trust and large faults large ones and thus slower recovery of faults. Plus, varying magnitudes of faults diminish trust more than large constant ones. When people have prior knowledge about faults, these do not lead to diminish of trust. This relates to the notion of system predictability, where an understanding of the system leads to higher trust. At the same time, automation successes will increase the trust in automation and automation failures decreases trust, while trust decreases faster than it increases. While trust decrease due to an automation failure is faster if the final outcome of a task is undesirable, the opposite it not true. Trust will also increase if the human fails without the automation, while the opposite is only slightly true [15].

Regarding properties of the trustor, there is some empirical work about the propensity to trust [12]. People trust automation less, if doing so increases the probability of negative consequences. After trust dissolution, trust recovery also takes longer in riskier situations than in less risky situations. Trust is more resilient when the reliability of the automation is high at the beginning and then decreases when compared to when it is low at the beginning and then increases.

[12] distinguish two types of human robot interactions: performance-based interactions (e.g., UAV performing surveillance and recognition of victims in a SaR mission), while here trustors are considered as operators (humans controlling the robot) and social-based interactions (how a robot can influence a human to e.g., take medicine or do useful exercises), where trustors are considered to be humans whose beliefs and behaviours are influenced by the robots. In performance-based interactions, opposite of the experimenters' hypothesis, people seem to overtrust robots in a fire emergency situation, even though the robots showed several faults (e.g., running in circles) (trust rating and trust behaviour not consistent). In social-based interactions, the decision of the human to comply or not comply is depending on whether this request is revocable or irrevocable. In addition, the appearance of the robots also play a role in trust: People place more qualities into robots that look more anthropomorphic, as well as animacy and intent. Moreover, people are less inclined to anthropomorphise when robots make mistakes [12].

[14] define trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability". While human-automation interactions can be described with trust, there are some differences between interpersonal trust and trust in automation. Between humans, trust emerges after recurrent interactions. At the same time, how one is perceived by the other influences one's behaviour (trust as self-fulfilling prophecy). As for decision-making in general, self-confidence is important and influences trust and reliance on automation.

IV. METHODOLOGIES

In this research, an indoors emergency evacuation model is constructed that simulates the process of people evacuating from a disaster scene. This evacuation model is an ABM: The agents in an ABM interact with the environment and with each other based on a set of pre-defined rules. These rules as well as the characteristics of the agents are derived from the modellers induced observations of the real world [16].

In this research, these rules are implemented by integrating the BDI framework with GT. Combining these two concepts allows to model the process of human decision making in more detail. This section thus motivates the choice for these two modelling techniques and first introduces the applied BDI framework. Some background is given on the rules that are implemented in an ABM to model the behaviour of the evacuating humans. Second, GT is explained.

Its integration with the BDI framework, as well as some of the used formulas are given. This allows to answer the first RQ about how to integrate GT into BDI. In the model, there are (1) the humans trapped in the disaster setting and aiming at evacuating the building as fast as possible and, (2) the evacuation robots that assist these humans in evacuating from the disaster scene.

Depending on the success of the previous interactions with a robot, a human will adjust the level of trust it has in this particular and also all other robots. Thus, this section ends with explaining the concept of trust in human-robot interaction, as well as the dynamics of trust over time. This way, the third RQ can be addressed, about modelling the interaction between evacuees and SaR robots.

A. BDI Model

Microscopic models aim at representing the interactions between humans. As opposed to macroscopic models, they enable to analyze how, in a multi-actor system, a overall behaviour emerges from these individual interactions. This makes it also possible to explain how a system of humans adapts and changes over time and how disruptions and external factors can affect this system. This is not possible with macroscopic models, in which institutional rules restrict the possible range of actions of the actors [17] . Hence, as an evacuation scene can be described as individual interactions giving rise to a global pattern, a microscopic model is needed.

Microscopic models are often implemented as ABMs [18], [19]. An ABM is a computational tool for modelling geo-spatial systems, that is systems, that are changing in time and space. An evacuation setting can be described as such a system and thus, an ABM is a natural choice. An ABM relies on pre-defined rules that the modeller infers from the real world to represent how the agents in the model behave in the environment. There are several ways of how these rules are inferred, while in many frameworks to build ABMs, incorporating psychological and emotional factors remains a challenge [20].

One of these, the BDI framework, reflects the research in [21] into human practical reasoning and the planning theory of intentions, which is able to address this challenge. The BEN model (behaviour with emotions and norms) from [22] is a BDI model that includes emotions (personality, social relationships, emotional contagion) and norms (laws, obligations) to an agent's evacuation behaviour. The IMPACT model from [4] uses the BDI framework to model socio-cultural, cognitive and emotional factors of evacuation behaviour.

Thus, this study also uses the BDI framework to model human evacuation behaviour, as it has been used in the past to model human behaviour in evacuation settings, taking into account a larger degree of the complexity of human decision making, than other techniques.

Humans in the BDI framework are referred to as agents and have the following features [23], [24]:

- They have beliefs about the state of the world. These beliefs can change and new beliefs can be added to the belief set as the system changes.
- Desires can be compared to values, and reflect the motivation of an agent, hence situations that the agent would like to happen. An 'activated' desire can be seen as a goal, namely a desire the agent is currently committed to.
- Finally, intentions reflect what an agent has chosen to do and thus represent desires to which agents have committed to. In order to achieve an intention, several plans are needed, representing sequences of actions that an agent takes.

By using the BDI framework to model the ABM's agents, the process of making a plan and executing this plan can be considered specifically. This way, an ABM that models the interactions between the different agents does not only capture the emerging actions from these intentions, but with the BDI framework also captures how these interactions come about. Hence, when using the BDI framework for ABMs, the inductive modelling process and the modeller's assumptions can be backed by a theory to describe how humans reason and plan. In this research, the implementation of BDI rules into the ABM is based on [4].

In the ABM, there is a given percentage of children, adults, and elderly people (male and female) with different speeds, compliance, and familiarity with the environment [4]. They have one of the following four different characters, ranging from very selfless to very selfish (the altruists, the selfless, the egoists, and the selfish) [25], which determine what game theory strategy they will take. At the beginning of the simulation, agents are randomly distributed in the environment and randomly assigned to groups of 1, 2, 3 or 4 people. Group members are linked, meaning that they have a relationship with each other. This means that those agents are for instance families, relatives, or friends, while no distinction is made between these. It is assumed that agents in a group will assist each other during the evacuation process.

The simulation environment, in which agents are located is described as a neighbourhood, through which they can move throughout the simulation. An agent can interact with other agents in the neighbourhood.

1) Belief: Based on their perception of all other agents' fear and their own fear, agents will believe whether or not there is danger. This represents the concept of social contagion [4] According to this concept, perceiving other agents that believe that the situation is dangerous will thus increase the belief about danger, which an agent attributes to a specific situation.

2) Desire: An agent's desire is either to continue walking around randomly or to start to evacuate, depending on how strong their belief of danger is and depending on their character. The altruists and the selfless agents will continue to walk around randomly for longer, in search of other agents to help. The selfish and the egoist agents will desire to evacuate as soon as possible to safe themselves.

3) Intention: When the desire of agents is to evacuate, an agent's intention is to get to the nearest exist as soon as possible. Whether or not an agents finds this nearest exit depends on the agent's familiarity with the environment. This binary variable describes whether or not an agent is familiar with its surroundings. An agent is either familiar with the environment, or not. If the agent is familiar with the environment, it is aware of where the nearest exit it to be found (e.g., an emergency exit). If the agent is not familiar with its surroundings, it is only aware of the main entrance, through which the agent has entered the environment. An agent's familiarity with the environment can change, when there is an evacuation robot present in the agent's field of view, of course only if the agent trusts the robot. If the agent does not trust the robot, it will not accept what the robot suggests and thus not become familiar with the environment. Every agent will always be aware of the main entrance, as this is the entrance, through which they are assumed to have entered the room.

B. Non-Cooperative Game Theory

GT can be described as a set of mathematical tools that explain the interactions between various decision-makers [26]. As this is what this study aims at analysing the choice for GT is natural: It enabled to model and mathematically compute the values of the interactions and the decision-making of humans during evacuation settings.

A game refers to the representation of different strategies to achieve different outcomes based on a given situation and the values that the players in the game associate to the it. Players include all those agents that are engaged in the decision making process. Each player is assumed to be of bounded rationality, namely they want to maximise a certain utility, for which they have limited information to base their decisions on [17], [26]. Each player also has a set of moves or actions. The sequence of these actions in an iterative game (i.e., with multiple rounds) refers to their strategies and can be selected by the agent on the anticipation of the decisions of other players. The outcome of the game is the result of the combination of the strategies of all players. Each player prefers different outcomes and the value a player assigns to a particular outcome is called the payoff for that agent. The game is subject to rules, which limit the set of possible moves and actions a player can make.

A distinction can be made between cooperative GT and non-cooperative GT. Cooperative GT aims at analyzing the creation of coalitions that bring additional value for the individual players in these coalitions. In cooperative GT, collective action is considered and hypothetical values resulting from creating coalitions need to be derived and quantified [27], [28]. With this cooperative GT aims at calculating which player should cooperate with whom and how much each player should sacrifice for the the common interest of this coalition. Cooperative games can also be analysed using non-cooperative GT [26]. Here, only one player's individual actions and its individual utility are considered. This enables to analyse different strategic interactions amongst the players. As this study aims at modelling the emerging evacuation behaviour of humans in a disaster setting, the choice for non-cooperative GT is made. It allows to take into account actions of individual agents and how these lead to interactions with other agents.

For evacuation scenarios, non-cooperative GT has been used before. [29] and [30] model an indoor evacuation scenario in which a two player game determines who of the two can use the exit, while [31] use non-cooperative GT to explain how agents choose one out of multiple possible exits to leave a building. [32] model the interactions of agents with non-cooperative GT, where agents play against conflicting neighbours to reduce their evacuation time.

In this study, in an evacuation scenario, the utility is defined as getting out of the emergency setting as fast as possible and thus depends the distance to the nearest exit. Other aspects are also included in the utility, that depend on the GT character of an agent, such that the utility of selfless and selfish people will vary. A game is launched as a conflict that arises between two agents during the evacuation: If two agents with the intentions to evacuate get into each other's way, they need to decide who can take the next step first. To achieve this, the players have two options; cooperating with the other agent or fighting (which is called defecting in game theoretic speech). Each of these actions have different payoffs, depending on what they mean to the player and thus their character [17], [26]. These are the four different characters, corresponding to the classic Prisoner's dilemma. These are the altruists (cooperators), the selfless (tit-for-tat), the egoists (unforgiving), and selfish people (defectors) [25]. Whenever an agent gets into a conflict with another agent, all those agents that are in the same group as the agent in conflict move towards the scene of the conflict in assistance, as it is assumed that people that the agent in conflict has a relationship with always want to help the agent.

An agent with the intention to evacuate, moves into the direction of the exit. At each time step, this agent thus gets closer to the exit. The distance at time step k of an agent i to the jth exit with position r_j^{exit}, that the agent i is headed to, is given by:

$$d_{ij}(k) = ||r_j^{exit} - r_i(k)|| \tag{1}$$

where $r_i(k)$ is the position of agent i at time step k. An evacuating agent i gets into conflict with an evacuating neighbor l that is close to it. Then, the difference in the estimated evacuation time of these two conflicting agents for each time step is defined with the cost function taken from [32]. $v_i(k)$ denotes the speed agent i is moving with at time k.

$$\Delta u_{il}(k) = \frac{d_{ij}(k)}{|v_i(k)|} \tag{2}$$

This equation represents the utility that is at play in the evacuation game between conflicting neighbours that depends on the character of the agents (cooperator versus defector). The losing agent is hindered in its intention to move towards the nearest exit, as it first has to recover from the conflict. While not modelled explicitly, a conflict in reality will involve agents pushing each other and potentially falling, such that the loosing agent will need a couple of seconds to get up again and sort themselves. Thus, it loses precious time in the evacuation. It is also this time lost that represents the conflict cost t_d, by which the utility in Equation 2 is reduced in the case, where two defectors are in conflict with each other [32]. If two cooperators get into conflict, they share the utility in Equation 2. If a cooperator gets into conflict with a defecting agent, its payoff will be the negative of the utility in Equation 2 while the defecting agent will get the full utility.

C. Robots and Trust

The evacuation robots are placed randomly into the environment. It is their task to guide the agents out of the disaster scene. For this, they follow the 5 principles, as proposed by [33]. First, the robots should do no harm to humans, meaning that they should not hinder the evacuation and (accidentally) direct the evacuees to greater danger. Second, the robots need to communicate in a way that is understood by a wide range of different people. This includes the use of gestures, lights, and signs. They also should attract attention while keeping interaction with evacuees minimal in order not to make the evacuees precious lose time during these interactions with the robots. Finally, they should help as many people as fast as possible to evacuate the disaster scene. The model of the robots is fairly simple. It is assumed that when an agent with the intention to evacuate perceives a robot within its field of view, this robot will show this agent the nearest exit, towards which the agent will then move. Thus, they will influence the familiarity variable of the agents.

The level of trust of an agent into a robot can change during the evacuation [12], [15]. Initially, the trust is equal to an agent's propensity to trust [12], which is a fixed character trait of each agent. Every agent has a different propensity to trust [12], [13]. The maximum initial trust of an agent in a robot cannot exceed its propensity to trust a robot. In order to evaluate trust of the evacuees into robots, three levels of robot failure are introduced. To what extent the interactions between agents and robots are successful determines whether the trust of an agent in robots decreases or increases, with different rates. These rates are fixed character traits of the agents, but depend on the quality of human-robot interaction [14], [15].

V. Case Study

The goal of this research is to build a simulation model of an indoors evacuation setting with the assistance of evacuation robots. This simulation model aims at extending a pure BDI model with GT to better capture the nature of human decision making. With the built model as described in Section IV, this section starts with giving an overview of the experiment set up of the case study. Then, the results of implementing GT within the BDI framework are introduced. These results need to be validated because it needs to be established to what extent this case study captures reality. For this, the model is compared to an existing benchmark, this being the Impact model from [4]. These steps aim at proving an answer to the second research question, namely how to integrate GT into BDI and to evaluate the added value of doing so.

The Impact model is a BDI model that has been validated against data stemming from an evacuation drill with the EXODUS model [34], [35]. The EXODUS model is described in literature as extensively qualitatively and quantitatively validated [36]. The Impact model is an ABM using the BDI framework to model the evacuation behaviour of a crowd of people from a transport hub. The model includes different factors that aim at fully capturing human decision-making, such as cognitive, emotional and socio-cultural factors. Validation is done by comparing the resulting evacuation time that the GT-BDI model produces to the evacuation time as calculated by the Impact model in similar settings.

In the next step, with a validated model, it can be analysed how the deployment of evacuation robots makes a difference in the evacuation process.

For this, a varying number of robots in varying failure states are introduced in the disaster setting. Evacuation times as well as trust over time of the victims in the robots are measured to estimate to what extent these robots affect the success of an emergency evacuation. These steps allow to answer the fourth research question, about how to model evacuation robots and to evaluate the influence of their presence on the evacuation process. The code needed for these analyses can be found in the following Repository.

A. Set Up GT-BDI

The model was built using NetLogo 6.3.0. Data analysis is conducted with Python. The computer used to run the simulations is a MacBook Pro from 2014 with a 2.2 GHz Quad-Core Intel Core i7 Processor and memory of 16 GB and 1600 MHz DDR3.

The evacuation environment consists in a square room with four doors in each wall as can be seen in Figure 1. This represents a room of 20x20m. At the beginning of the simulation time, 600 agents are placed randomly in the room. The size of the agents equals a quarter of a patch in the NetLogo environment which corresponds to a square of about 0.27x0.27m. The agents have an observation distance of 5m. The main entrance, through which the agents had accessed the room is the lower one. The remaining three doors are emergency exists, of which the agents might or might not be aware, depending on their familiarity with the environment. The doors are 4m wide [4].

At the outset of the simulation time, a fire breaks out. The location of the outbreak of the fire is random. The fire has a radius of 3m. The fire does not propagate during the simulation time and is static. When agents get stuck in the fire, they die. After the fire has erupted, the evacuation time starts with the first agent noticing the danger and starting to evacuate. The evacuation ends, as soon as all living agents have either left the room through one of the four doors.

TABLE I
PARAMETER SETTINGS FOR VALIDATION OF THE MODEL

	Setting 1	Setting 2
Familiarity	0%	50%
Duration of conflict t_d	30s	see Table II
Percentage children	15%	15%
Percentage elderly	15%	15%
Percentage females	50%	50%
Fire location	Random	Random
Initial victim location	Random	Random
Group 1 person	100%	50%
Group 2 people	0%	25%
Group 3 people	0%	15%
Group 4 people	0%	10%

TABLE II
GAME THEORY PARAMETER SETTINGS

	Min	Max	Increment
Defectors	10%	20%	5%
Unforgiving	35%	45%	5%
Tit-for-Tat	25%	45%	5%
Cooperators	10%	20%	5%
Duration of conflict t_d	5s	30 s	10s/15s

All parameters characterising the agents are kept constant during the simulation time. To make comparison to the benchmark possible, Setting 1 of the model is inspired in [4] and given in Table I. In Setting 2, other aspects are taken into account that enable to analyze the added value of integrating GT and BDI.

For validating the model, in Section V-C1, simulation runs are conducted without evacuation robots. Only parameters relevant for the implementation of GT are changed, these being the distribution of character traits in the agent population and the duration of a conflict between agents (see Table II. The distribution of character traits will affect the choice for GT strategies of an agent and thus its resulting evacuation time. The duration of a conflict will also affect the agents' evacuation times. It is assumed that the longer the conflict, the longer the resulting evacuation time. The conflict duration is seen as the entire duration from engaging in a conflict, until an agent has recovered from the conflict (e.g. getting up after being pushed and having fallen down). Therefore, the conflict duration is set to a random duration of a maximum of 30 seconds, which corresponds to the maximum falling time of [4]. Agents get info conflict with other agents that are within a distance of 40cm from it.

This set up thus relies on the following set of assumptions:

A1: The fire that breaks out in the beginning of the simulation time is static. Neither does it propagate, nor does the smoke resulting from the fire influence agents' health.

A2: Agents are either familiar with the environment or not. In case they are not, they are still assumed to be aware of the main entrance through which they accessed the room.

A3: Agents that get caught in the fire die.

A4: Agents' characteristics (i.e., game theory profile) are assumed to be constant during the simulation time.

A5: Conflict time is randomly assigned to a particular conflict, unrelated to the agents associated with it.

B. Set Up Robots

For modelling evacuation robots in Section V-C2, the GT parameters from the validation process are chosen as these are established to be the closest to reality. The parameter specifications can be seen in Setting 2 of Table I. The model environment remains unchanged and simulations are run on the same computer.

TABLE III
ROBOTS AND TRUST PARAMETER SETTINGS

	Minimum	Maximum	Increment
Robots	10	100	45
Trustiness	0.75	1.5	-
Trust recovery	0.1	0.2	-
Trust decrease	0.15	0.3	-
Failing robots	0	70%	0.35%

Different simulations are conducted to account for uncertainty in the trust dynamics of agents into robots. It is assumed that if trust increases and recovers faster after successful interactions than it decreases after unsuccessful interactions, the total evacuation time will be shorter. Every agent has a trustiness, a propensity to trust the robots. If this is greater than 1, agents are assumed to be overtrusting. If it is smaller than 1, agents are sceptical. At the outset of the simulation, the agents' the level trust is equal to their trustiness (see Table III). During the evacuation, agents will interact with robots in their field of view. The robots are assisting the agents in finding the entrance that is closest to them. Thus, the level of trust changes; it either increases (with a rate equal to the trust recovery) or decreases (with a rate equal to the trust decrease), depending on the failure of the interactions this agent has with robots. [12], [13].

There are different levels of failure, which affect trust differently. A level 1 failure represents the lowest level of failure of interaction with the robots. This can be understood as a flickering light or an audio that is off. When an agent meets a robot with a level 1 failure, the agent's trust is reduced by the trust decrease. A level 2 failure represents failures, that are slightly more severe. This could be a robot that is not working at all anymore and is of no use to the agent. When an agent meets such a robot, the agent's trust is reduced by twice the trust decrease. Finally, a level 3 failure represents the most severe and dangerous level of failure. This is a robot that is giving wrong indications to the agents, which will mislead the agents. When an agent meets such a robot, the agent's trust is reduced by three times the trust decrease. Depending on the severeness of the failure an agent encounters, trust in robots also recovers again. When an agent encounters a fully functioning robot, its trust in evacuation robots increases by the trust recovery. While the number of failing robots is varied per experiment according to Table III, the state of failure (i.e., 1 to 3) is determined randomly.

A successful interaction with a robot is thus one with a robot that is intact and the interaction between the robot and the agent has not failed in any way. As a result of this interaction, the agent will be evacuating faster and gain a couple of seconds of evacuation time. After a successful interaction, the trust of an agent in a robot is increased again (trust recovery). An unsuccessful interaction is one, where an agents encounters in its field of view a robot that has failed in one of the three different failure stages, as outlined in Section IV. The rates for increase and decrease of an agent's trust in a robot are uncertainties in the model and are varied according to the variable "trust recovery" and "trust decrease" in Table III [14], [15].

This set up relies on the following list of assumptions:

A1: Agents are aware of the fact whether or not a robot is faulty.
A2: Faulty robots can still move across the room.
A3: If an agent has an unsuccessful interaction with a robot, this agent's trust in all robots in the environment decreases and not only its trust in this particular robot with which it had an unsuccessful interaction.
A4: The success of a human-robot interaction solely depends on the robot and not on the human.

C. Results

In order to answer the research question of whether extending a BDI model with GT leads to a more accurate evacuation modelling, this section first presents the results of combining BDI and GT into one model. For this, simulations were conducted with varying parameter combinations, to account for randomness and uncertain parameter values. These are, to name a few, the exact location of the fire and the initial location of the agents, as well as the distribution of GT character traits amongst the distribution of agents that are present on the disaster setting. These simulation runs allow for the validation of said model. Validation is conducted by comparing the different model runs with the benchmark. Then, evacuation robots are added to the disaster setting. Different simulation runs are again conducted to account for uncertain parameter values. These concern mostly the level of trust and the dynamics of the agent's trust into robots. These results give an indication about whether the presence of these robots can improve the evacuation time.

1) Combination GT and BDI: To see the effect of using game theory to capture how humans take decisions during an evacuation as explained in Section IV, experiments in this section are first conducted without evacuation robots. The character traits (selfless to selfish) are distributed as indicated in Table II. It is assumed that there are less people that have extreme character traits and therefore, there are less defectors (totally selfish) and less cooperators (totally selfless) than the more balanced characters. In Figure 1, the game theory character traits are represented by the colour of each agent. A blue agent is a cooperator, a red agent is a defector, an orange one is an unforgiving agent and a tit-for-tat agent is represented by turquoise. The duration of a conflict is also an uncertainty in the model. For this, the model is ran with three different maxima of conflict durations, from short conflicts of a maximum of 3 seconds, to conflicts of a maximum of half a minute to long conflicts of a maximum of 30 seconds. As not all conflict has an equal duration, each agent is then assigned a random conflict duration with as upper bound one of these maxima.

Each experiment setting (i.e. each model run with a different distribution of game theory parameters) is repeated for 60 times to allow for some variation in the results due to random parameters, such as the location of the fire and the initial random locations of the victims. This leads to a total of 3240 runs.

Running the experiments in the settings from Table II, it can be seen that implementing game theory into the BDI model has an impact on the evacuation time. The boxplot plot in figure 3 represents the distribution of the different evacuation times that result from the model runs in the different configurations.

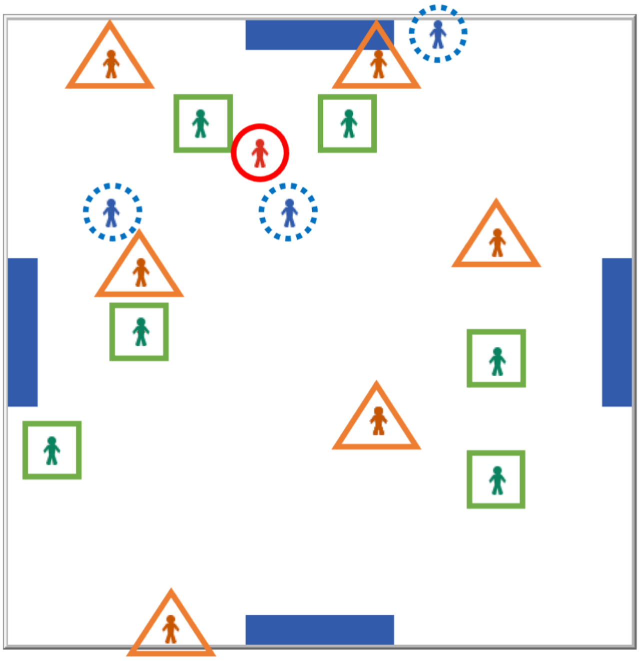

Fig. 1. Initial placement of 20 agents before a fire breaks out. The blue squares along the walls represent the exits. The lower exit is the main entrance through which the agents are assumed to have entered the room. The colors of the agents indicated their GT character. Forms are added for additional distinction, but are not included in the model. The cooperators are in blue dashed circles, the defectors are in red circles, the unforgiving are orange triangles and the tit-for-tat'ers are turquoise squares.

The average evacuation time of the GT-BDI model in Setting 1 from Table I is 466.92 seconds, which is very close to the results of the Impact model, but slightly worse in performance when compared to the EXODUS model (see Table IV). The minimum is given by 423.18 seconds, the maximum with 504.31 seconds and the lower and upper quartiles with 449.36 seconds and 490.18 seconds respectively.

When running the GT-BDI model in Setting 2 from Table I, the average evacuation time is of 499.17 seconds and from the boxplot plot can be seen, that the minimum is given by 455.25 seconds and the maximum is an outlier of 560.57 seconds. The lower an upper quartile are given by 486.18 seconds and 512.67 seconds respectively.

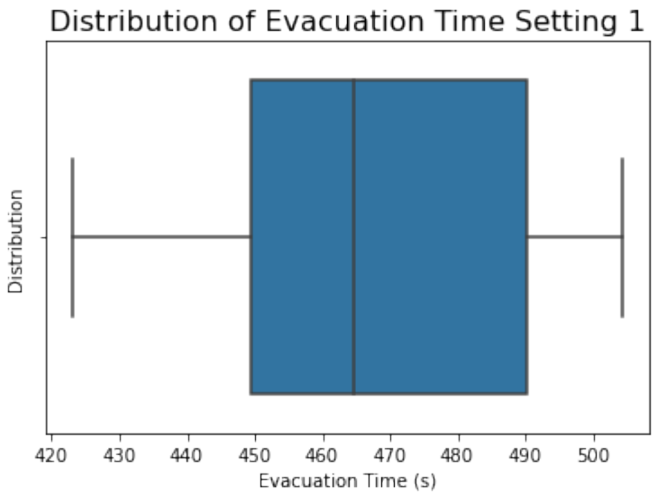

Fig. 2. Distribution of evacuation times when running the GT-BDI model in Setting 1

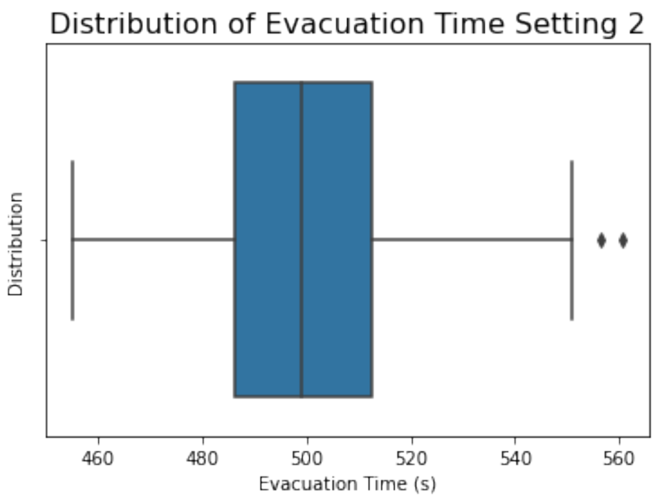

Fig. 3. Distribution of evacuation times when running the model in Setting 2

Depending on the parameter settings and on the distribution of characters of the GT-BDI model, the latter is able to result in evacuation times that are more realistic (see Table II). When running the GT-BDI model in Setting 2, there are thus some specific combinations of the 26 possible combinations of character traits that do lead to evacuation times closer to the EXODUS model, which is of 585 seconds than a purely BDI-based model (being the

TABLE IV
COMPARISON TO BENCHMARK WITH NO ROBOTS. BOTH THE AVERAGE OVER ALL SCENARIO AS WELL ARE THE AVERAGE OF THE SCENARIOS THAT PERFORM BETTER THAN THE PURE BDI MODEL ARE GIVEN

	EXODUS	Impact	GT-BDI Setting 2	GT-BDI Setting 1
Total	585s	516.6s	499.17s	466.9s
Relative Diff	–	11.69%	14.67%	20.19%

Impact model on its own, without any game theory, which reaches 516.6 seconds). Those scenarios represent 19.75% in total. Here, adding GT can bring the resulting evacuation time closer to the EXODUS model. The scenarios, in which the evacuation times come closest to reality are given on average in Table VI. Here, the resulting simulation time results on average in 533.12 seconds.

It can be seen that the number of victims that are not successfully evacuating varies per character trait. The average success per game theory character when running the GT-BDI model in setting 2 is summarized in Table V. In Figure 4, a boxplot of the distribution can be found. The average success per character from Table V is represented in the box plots as the bar in the box. This allows to estimate the range of the results. For the cooperator profiles, the success of an evacuation is bounded by the lower quartile in the boxplot of 96.47%. The upper quartile is given by 96.89%. The minimum is 95.81% and the maximum is 97.58%, which are both outliers. When looking at the success of evacuating agents with a tit-for-tat profile, it can be seen that the lower quartile of the distribution is also bounded by 95.83%. The upper quartile is 96.17%. The maximum is an outlier of 96.90% and the minimum 95.44&. The unforgiving agents have a minimum of 95.45% and the maximum is 96.70%,

TABLE V
SUCCESS OF EVACUATION PER CHARACTER TYPE WITH NO ROBOTS PRESENT

	Successfully evacuated
Defectors	96.61%
Unforgiving	95.91%
Tit-for-Tat	96.01%
Cooperators	96.69%
Average	96.32%

which both are outliers. The lower and upper quartile are of 95.83% and 96.06%. Defectors reach a lower and upper quartile 96.44% and 96.06%. Here, the minimum is 95.88% and the maximum is an outlier of 96.94%. It can be seen that the cooperators have the greatest interquartile range and the unforgiving the smallest range.

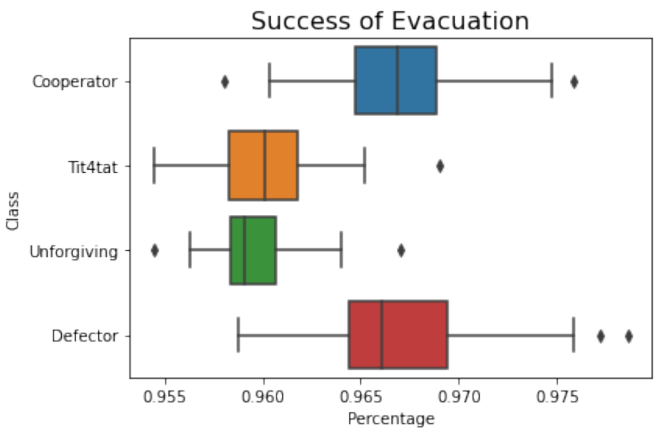

Fig. 4. Percentage of successfully evacuated agents depending on their game theory character traits

The different conflict durations also seem to have impact on the average evacuation times when running the GT-BDI model in setting 2, as can be seen in Figure 5. Interestingly, the average evacuation time is shortest, when the conflicts are allowed to last up to half a minute, the average evacuation time is given by 492.12 seconds. In the scenarios, where conflicts take up to 5 seconds, the average evacuation time is 503.05 seconds. Evacuations, where conflicts last for maximum 15 seconds take for 507.25 seconds on average. However, it is interesting to note that in those scenarios, where the GT-BDI model performs closest to the EXODUS model, the average conflict duration is actually 15.63 seconds. In fact, in 31.25%, the conflict time was of only 5 seconds, in 43.75% it was 15 seconds and in 25% it was 30 seconds.

At the same time, the number of conflict also varies for different conflict durations. For long conflicts, there are 6781.76 conflicts. The average evacuation time for long conflicts is 492.12 seconds. For conflicts of a duration of 15 seconds, there are 6862.37 conflicts and an average evacuation time of 507.25 seconds. The short conflicts lead to 6807.49 conflicts and with an average evacuation time of 503.05 seconds. This translates to one conflict every 50 seconds per agent, such that each agent is roughly engaged in 10 conflicts during the entire evacuation process.

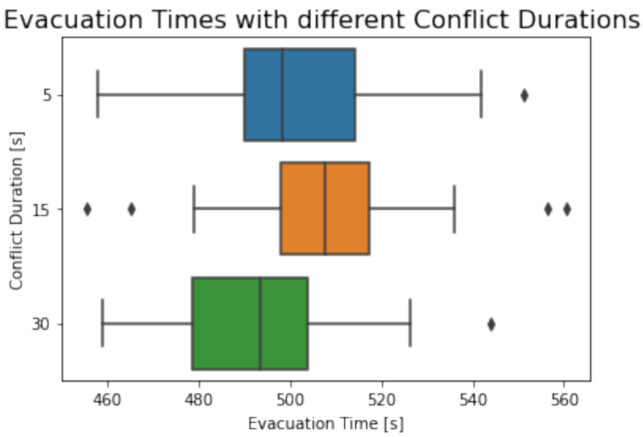

Fig. 5. Distribution of evacuation time for the three different maximum conflict durations

2) Evacuation Robots: To evaluate to what extent the deployment of robots influences the evacuation, experiments are conducted with a varying size

TABLE VI
AVERAGE GT PARAMETERS OF THE SCENARIOS THAT LEAD TO THE MOST REALISTIC EVACUATION TIMES

	Best scenario
Defectors	16.56%
Unforgiving	34.06%
Tit-for-Tat	35.31&
Cooperators	14.06%
Duration of conflict	15.63s

of robot fleet with evacuation robots with varying degrees of failures. In Figure 6, the initial placement of agents and robots can be seen. Before the fire breaks out, all robots are green in colour, which means that they are all fully functioning. After the fire breaks out and during the evacuation, a given number of robots will break and fail randomly in three different stages, which will impact the trust of the agents in the robots, as outlined in Section IV. In the first set of experiments, the robots will be stationary. This means, that they will stay on their initial position and will not move during the evacuation. In the second set of experiments, the evacuation robots will move. From their initial position, they will have a random heading and moving randomly through the disaster setting, avoiding the fire. By moving through the room, it is assumed that they will encounter more victims and thus be able to assist more people to evacuate from the fire.

For these experiments, the character distribution as in Table VI is taken since this corresponds to the validated model and led to the evacuation time that come closest to reality as established by the EXODUS model. Then, the number of robots is varied with a minimum number of 10, a medium number of 55 robots, and a maximum of 100 robots per experiment. With 10 evacuation robots, each

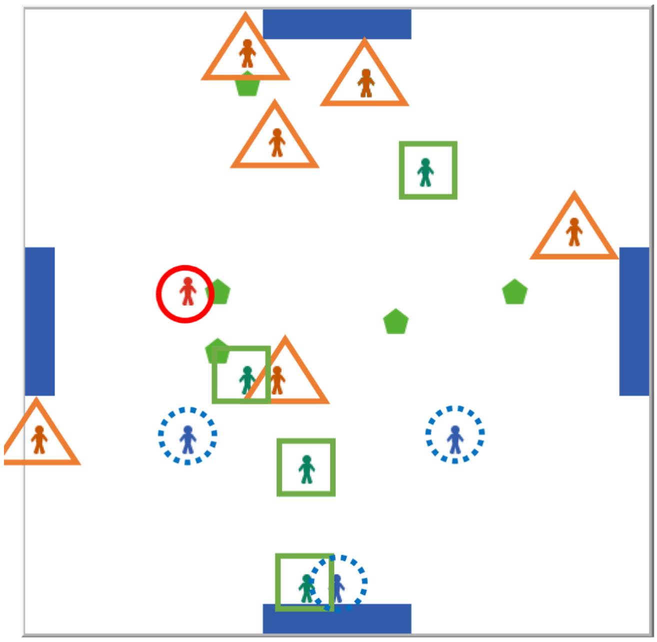

Fig. 6. Initial placement of 20 agents and 5 robots before a fire breaks out. The evacuation robots are represented by the green pentagons.

robot is supporting about 60 of the total 600 agents present. With 100 evacuation robots, each robot takes care of 6 agents in the evacuation setting. This, together with varying the trust parameters, leads to a total of 4320 experiments, as each experiment is repeated 60 times to account for the randomness introduced in the model as described in Table I. These 4320 experiments are first conducted with stationary robots.

Different levels of trust can be found, depending on the number of present robots and the trustiness of the agents. The measured levels of trust represent the average values of trust of all agents, averaged over the simulation time. In Figure 7, it can be seen that more robots lead to a higher level of trust in the latter. When having 100 robots, the average level of trust amounts to 0.41, as opposed to 0.32 with 55 robots and 0.20 with 10 robots.

Different amount of failed interaction surprisingly

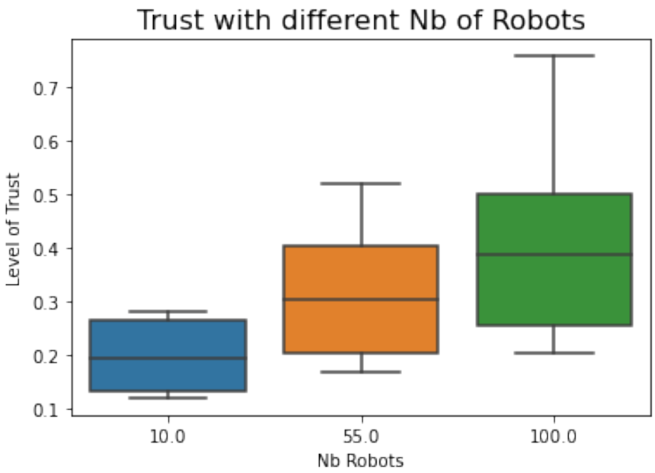

Fig. 7. Distribution of level of trust when varying the amount of stationary evacuation robots

only have a small affect on the level of trust (see Figures 8). Still, when having only successful interactions, the average level of trust equals to 0.37, 35% unsuccessful interaction leads to an average level of trust of 0.29 and 70% unsuccessful interactions to 0.27. It can be seen that the difference between only successful and a small number of unsuccessful interactions is larger than between a small number and a large number of unsuccessful interactions.

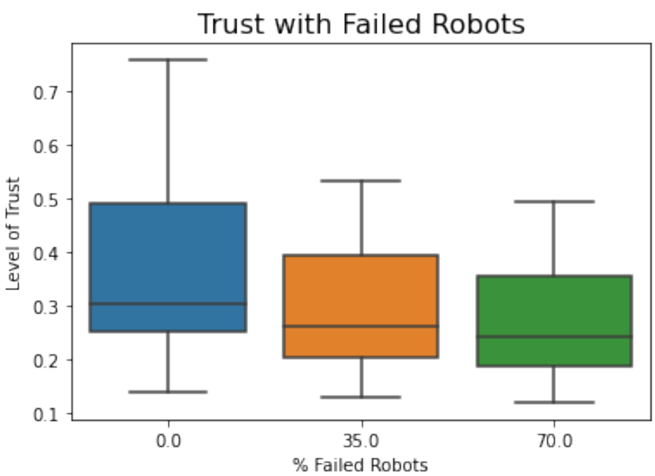

Fig. 8. Distribution of level of trust when varying the amount of failed stationary evacuation robots

TABLE VII
LEVELS OF TRUST DEPENDING ON DIFFERENT VALUES OF TRUSTING PARAMETERS OF THE AGENTS IN STATIONARY EVACUATION ROBOTS

	Trust for Low Value	Trust for High Value
Trustiness	0.21	0.41
Trust decrease	0.32	0.30
Trust recovery	0.30	0.31

A larger effect can be found when relating the trustiness of the agents to the resulting average level of trust (see Figure 9). It can be concluded, that a high trustiness, which relates to a high propensity to trust and thus a high initial level of trust of the agents in robots, also leads to high overall levels of trust. A trustiness of 1.5 leads to average levels of trust of 0.41 and a trustiness of 0.75 to 0.21.

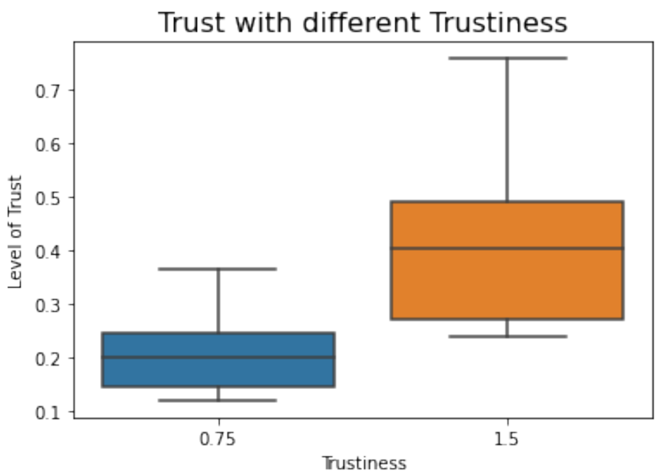

Fig. 9. Distribution of level of trust when varying the trustiness of the agents in stationary evacuation robots

Trust decrease and trust recovery do not have a large effect on the resulting levels of trust (see Table VII). The values for low and high trust parameters are for the trustiness 0.75 and 1.5, for the trust decrease 0.15 and 0.3 and for the trust recovery 0.1 and 0.2.

The evacuation time is significantly reduced compared to the average evacuation time when there are no robots present, which was 499.17 seconds or 533.12 seconds with the same average GT character trait distribution. The distribution of evacuation time in function of the number of present robots can be seen in Figure 10.

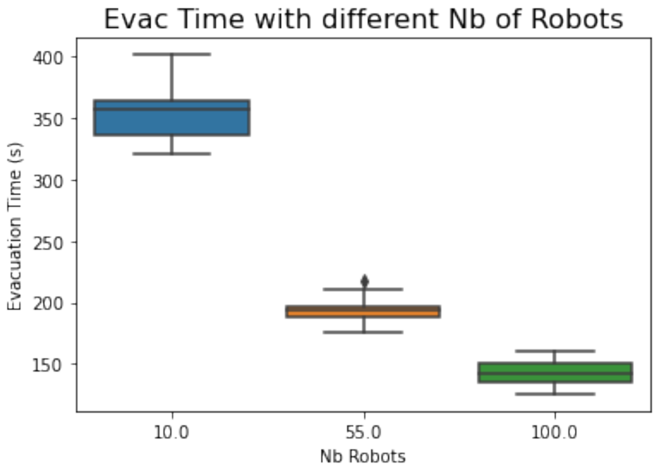

Fig. 10. Distribution of evacuation time when varying the amount of stationary evacuation robots

The figure shows, that having a large number of robots (e.g., 100 robots) leads to an average evacuation time of 143.37 seconds, which is less than half of the evacuation time without robots. A medium number of robots, this being 55 robots, still results in an evacuation time of 193.92 seconds. When having a small number of robots present, namely 10 robots, the evacuation time is 353.43 seconds. It can be seen that the difference in evacuation time in having 10 as opposed to 55 robots is greater than the difference between 55 and 100 robots.

When comparing the different evacuation times with varying the amount of failed interactions between agents and robots, one gets the distribution in Figure 11. Here, it can be seen that the difference in evacuation times is small. When having only successful interaction, the average evacuation time is 369.82 seconds. With at most 35% of the interactions failing, the mean evacuation time is 370.27 seconds and with at most 70% of the interaction failing, it is 401.57 seconds.

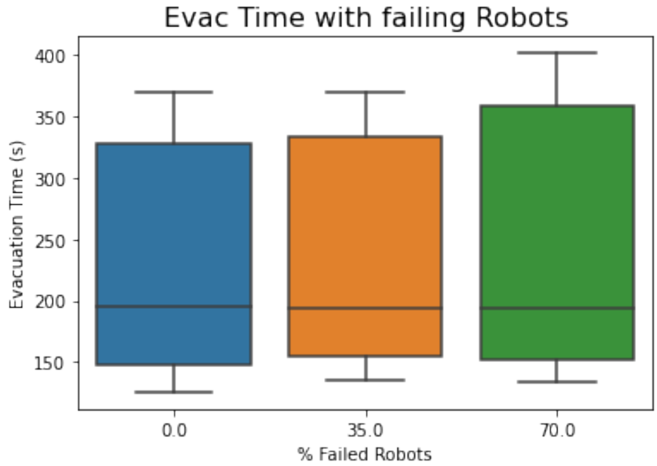

Fig. 11. Distribution of evacuation time when varying the amount of failing stationary evacuation robots

However, when relating the resulting evacuation times to the level of trust of the agents in the robots, one can see in Figure 12 that there is a relation. For this, the resulting levels of trust have been grouped into bins. This results in low, medium and high levels of trust with an average of 0.1842, 0.3507 and 0.5918 of trust of the agents in the robots. The figure shows, that a low level of trust leads to a higher average evacuation time of 260.76 seconds, a medium level of trust to 220.42 seconds and a high level of trust to 156.31 seconds.

With stationary robots, on average, 95.54% of the victims are evacuated successfully. The lower an upper quartile are given by 95.47% and by 95.61% respectively. The minimum and the maximum values are given by 95.32% and 95.71% respectively. It can be determined that these values are not spread a lot. In Figure 13, a boxplot shows this distribution in function of increasing the number of present

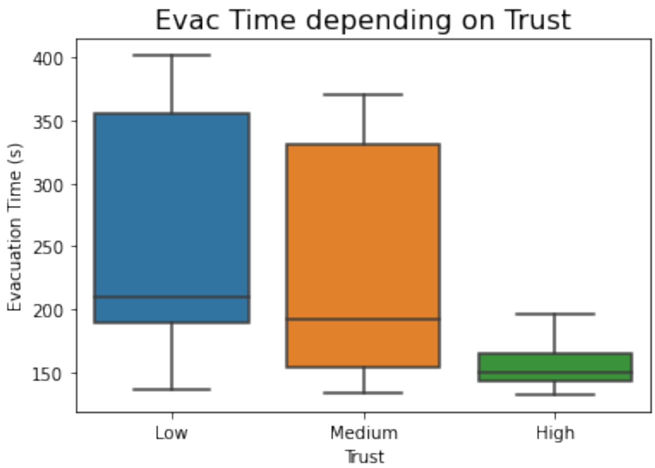

Fig. 12. Distribution of evacuation time with different levels of trust in stationary evacuation robots

TABLE VIII
SUCCESS DEPENDING ON DIFFERENT VALUES OF TRUSTING PARAMETERS OF THE AGENTS IN STATIONARY EVACUATION ROBOTS

	Success for Low Value	Success for High Value
Trustiness	95.54%	95.54%
Trust decrease	95.56%	95.52%
Trust recovery	95.53%	95.54%

evacuation robots. As can be seen in figure, there is not really a relation to be observed between a high or a low success and a high or a low number of robots. Also the failure of interactions does not have an affect. Neither the parameters trust recovery, trust decrease or trustiness seem to have an impact on the success of the evacuations when the robots are stationary (see Table VIII).

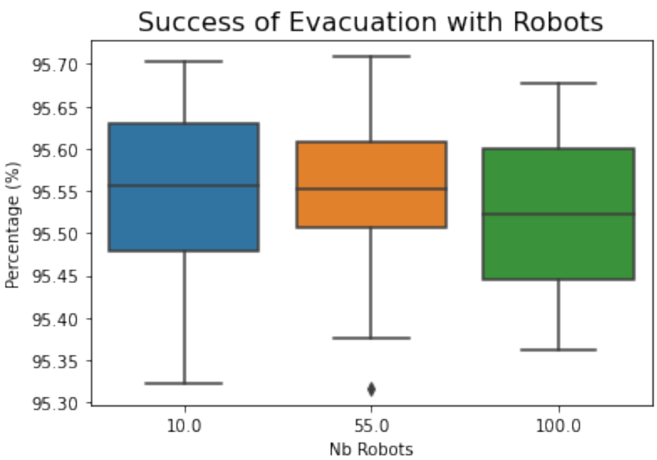

Fig. 13. Evolution of evacuation times when increasing the number of stationary evacuation robots

The same experimental set up is now used to conduct 4320 simulations, but now with moving robots. The number of robots is again varied with a minimum number of 10, a medium number of 55 robots, and a maximum of 100 robots per experiment. The robots are now randomly moving around in the room during the evacuation. Their initial placement is random and their heading as well. They move, avoiding the position of the fire, until all victims have successfully evacuated. While moving, a given number of the robots will break and lead to failed interactions with agents as explained in Section IV.

With moving robots, there are also different levels of trust in relation to the number of robots present, as can be seen in Figure 14. Again, the more robots, the higher the trust When having 100 robots, the average level of trust amounts to 0.47, as opposed to 0.43 with 55 robots and 0.27 with 10 robots. All these trust values with moving robots are slightly higher than their equivalent values with stationary robots. When comparing Figures 14 and 7, it can be seen that when having moving robots, the levels of trust that are attained are overall higher.

Again, different numbers of failing interactions have little effect on the level of trust (see Figure 15). When having only successful interactions, this leads to an average level of trust 0.50, having 35% unsuccessful interaction to 0.36 and 70% unsuccessful interactions to 0.29. Here as well as with stationary

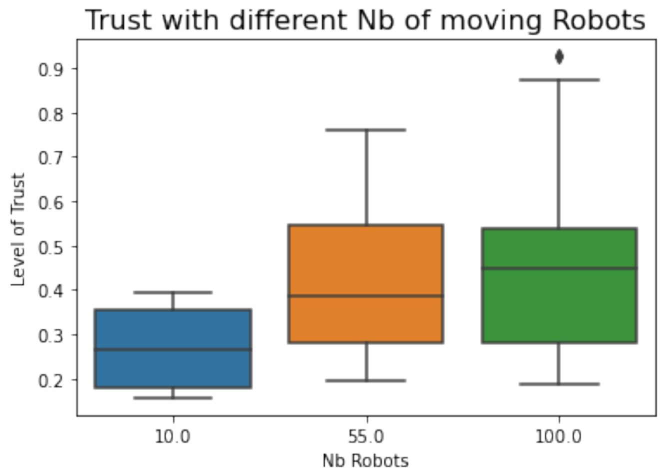

Fig. 14. Distribution of level of trust when varying the amount of moving evacuation robots

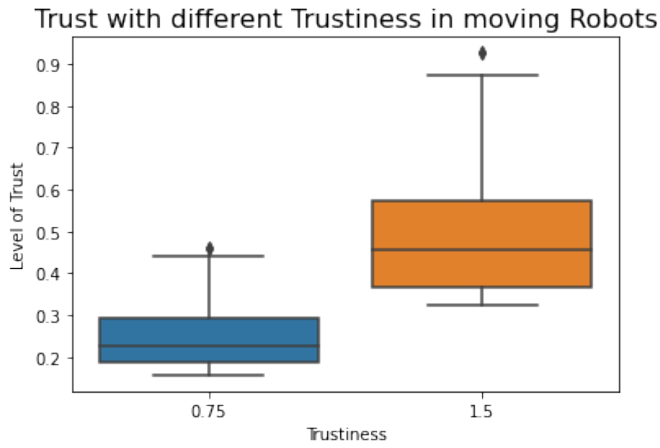

Fig. 16. Distribution of level of trust when varying the trustiness of the agents in moving evacuation robots

TABLE IX
LEVELS OF TRUST DEPENDING ON DIFFERENT VALUES OF TRUSTING PARAMETERS OF AGENTS IN MOVING EVACUATION ROBOTS

	Trust for Low Value	Trust for High Value
Trustiness	0.26	0.52
Trust decrease	0.40	0.38
Trust recovery	0.38	0.39

robots, the maximum levels of trust are achieved when having only successful interactions.

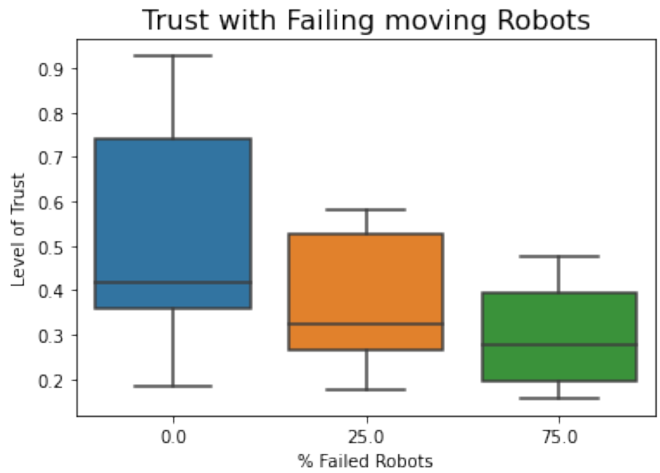

Fig. 15. Distribution of level of trust when varying the amount of failed moving evacuation robots

The trustiness of the agents has again a large effect on the resulting average level of trust (see Figure 16). A trustiness of 1.5 leads to average levels of trust of 0.51 and a trustiness of 0.75 to 0.25. The other two trust parameters (trust decrease and trust recovery) again do not have a large effect (see Table IX).

When looking at the resulting evacuation time, not only do they again decrease with an increasing number of robots. Also compared to stationary robots, moving robots lead to an additional decrease of the evacuation times. The distribution of evacuation time in function of the number of present robots can be seen in Figure 17. It can be seen that having 10 moving robots leads to an average evacuation time of 206.15 seconds, which is another gain of several seconds compared to having stationary robots (see Table X). 55 robots result in an average evacuation time of 91.39 seconds and 100 robots lead to 74.28 seconds.

When having moving robots, failing interactions seem to have less an effect as with moving robots. As can be seen in Table XII, the differences in evacuation times between having no failures and

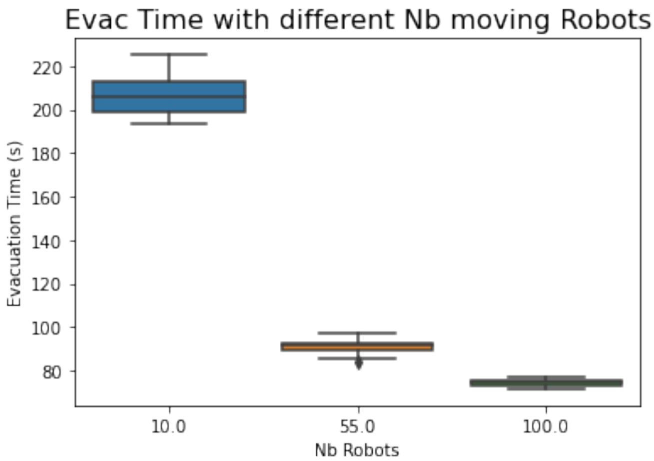

Fig. 17. Distribution of evacuation time when varying the amount of moving evacuation robots

TABLE X
EVACUATION TIMES DEPENDING ON NUMBER OF ROBOTS WHEN HAVING STATIONARY VERSUS MOVING ROBOTS

	Evac time with Stationary	Evac time with Moving
10 robots	353.43s	206.15s
55 robots	193.92s	91.39s
100 robots	143.37s	74.28s

25% is in both cases only a fraction of a second. Between 25% and 75%, the difference for stationary robots is larger, however, when compared to moving robots.

The level of trust of the agents in the robots, again, has an impact on the resulting evacuation times (see Figure 18). The levels of trust have been grouped into the bins, leading to low, medium and high levels of trust with an average of 0.1919, 0.3651 and 0.5830 of trust of the agents in the robots. For a low level of trust, the resulting evacuation time averages 156.12 seconds. Medium levels of trust leads to average evacuation times of 124.35 seconds while high levels of trust to 84.98 seconds.

TABLE XI
EVACUATION TIMES DEPENDING ON FAILURE OF INTERACTIONS WHEN HAVING STATIONARY VERSUS MOVING EVACUATION ROBOTS

	Evac time with Stationary	Evac time with Moving
0% failures	369.82s	122.61s
25% failures	370.27s	123.56s
75% failures	401.57s	125.64s

TABLE XII
EVACUATION TIMES DEPENDING ON LEVELS OF TRUST WHEN HAVING STATIONARY VERSUS MOVING ROBOTS

	Evac time with Stationary	Evac time with Moving
Low trust	260.76s	156.12s
Medium trust	220.42s	124.35s
High trust	156.31s	84.98s

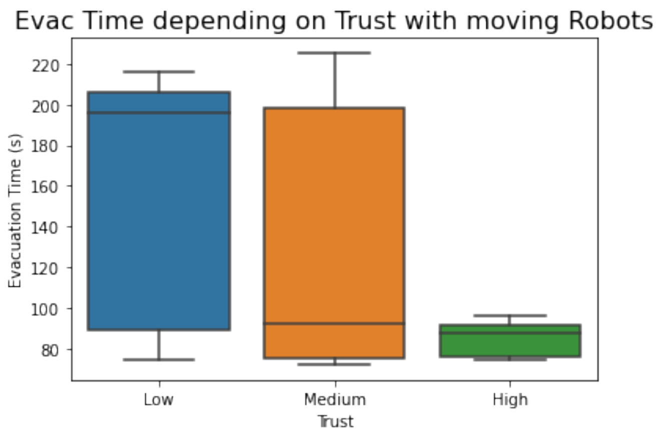

Fig. 18. Distribution of evacuation time with different levels of trust in moving evacuation robots

With moving robots, on average, 96.30% of the victims are evacuated successfully. This is slightly more than with stationary robots. The lower an upper quartile are given by 95.95% and by 96.53% respectively. The minimum and the maximum values are 95.53% and 97.28% respectively. These values are also a bit greater than with stationary robots.

In Figure 19, a boxplot shows this distribution

TABLE XIII
SUCCESS DEPENDING ON DIFFERENT VALUES OF TRUSTING PARAMETERS WITH MOVING ROBOTS

	Success for Low Value	Success for High Value
Trustiness	96.31%	96.30%
Trust decrease	96.31%	96.30%
Trust recovery	96.30%	96.30%

in function of increasing the number of present evacuation robots. As opposed to Figure 13 of stationary evacuation robots, there is a relation to be observed between a high or a low success and a high or a low number of robots. Having 10 robots leads to an average success of 95.69%, 55 robots to 96.33% and 100 robots to 96.33%. However, as with stationary robots also for moving robots, the other trust parameters, as well as the failure of interactions does not have an effect on the success of the evacuations (see Table XIII).

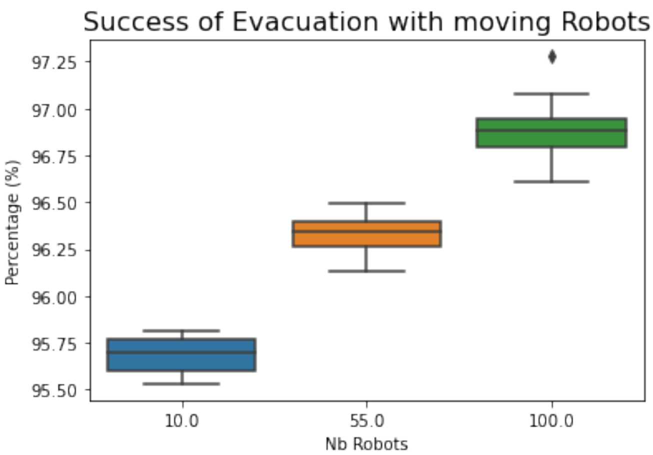

Fig. 19. Evolution of evacuation times when increasing the number of stationary evacuation robots

D. Discussion

After presenting the result of the constructed model and of the simulation runs in Section V-C, this section discusses the implications of these results. To begin with, the BDI model extended with GT was validated. The validation process will thus first be discussed as well as the added value of implementing and combining the BDI approach with GT. After validating this model, evacuation robots were added and it was analysed to what extent these affect the evacuation time of the agents from the fire. To evaluate the advantage of evacuation robots, the notion of trust was introduced in the model. Trust is a dynamic concept, which increases, decreases and recovers, depending on the success of an human robot interaction. Therefore, different modes of robot failures were introduced in the model and simulated. Hence, this section presents a discussion on modelling robots for emergency evacuation. Finally, this section finishes with a discussion on the limitations of the model and what further research these imply.

1) Validation of GT-BDI model: In order to validate the combined GT-BDI model, simulations are conducted with varying different parameters to determine which variable have an impact on the resulting evacuation times. The evacuation times the model produces are compared to the benchmark to determine the validity of these results (see Section V-C1). Parameters that are analysed are the conflict duration in the GT interaction between agents and the GT character distribution in the population. Then, the success and duration of the resulting evacuation was analysed.

Regarding the conflict duration, is is found that, contrarily to what could be expected, those scenarios, in which the evacuation time is most realistic (as established by comparing to the EXODUS model), shorter conflict duration actually can lead to longer overall evacuation times. In fact, one could assume, that if each conflict only lasts for a short amount of time (i.e., 15 seconds), the sum of all conflict durations is smaller and hence leads to a shorter evacuation. This, however, is not always the case. Indeed, the shortest conflict duration of 15 seconds can lead to longer evacuations and the longest conflict duration can lead to shorter evacuations. This leads to the conclusion that in those scenarios, the sum of all conflicts with the shorter conflict duration must be larger than if adding all the longer conflicts up. The only possible explanation for this is that there must be more conflicts arising when the duration of these are shorter. At the same time, there must be less conflicts arising, when they last for longer. This is confirmed when evaluating the number of conflicts that arise for each different conflict duration, where the same distribution can be seen. This makes sense, since if an agent is engaged in a conflict that takes longer, the same agent cannot be engaged in another conflict. Therefore, in the same amount of total time, there will be more conflicts if they are shorter and less conflicts if they last longer. Hence, when a conflict is over very fast, the two conflicting agents continue their evacuation and the chance of meeting another agent soon again with which to engage in a conflict is bigger. At the same time, if a conflict takes longer, the two conflicting agents only continue their evacuation later. During the time they had their conflict, the agents around them may have move further already. Therefore, their chances of meeting another agent soon to engage in a new conflict are lower. Thus, there will be less conflicts and the overall evacuation duration will be lower. However, this also depends on the initial locations of the agents in the room and on the distribution of character traits in the population of agents.

Then, character distribution is varied. Here, an impact on the success of the evacuations as well as on the resulting evacuation times is found. The success of an evacuation decreases when the number of victims dying in the fire increases. Fire victims are agents that get stuck in the position of the fire in the room. While the differences in successful evacuations were very small, the cooperators and defectors are slightly more successful in being evacuated than the tit-for-tat'ers and the unforgiving. The defectors are those agents that immediately start evacuating as soon as they perceive a fire and then only act in their advantage to leave the disaster setting. On average, the cooperators are the most successful in evacuating. It is interesting to note that they are slightly better than the defectors. The cooperators, as the altruistic agents do not immediately evacuate but first continue to walk randomly across the room in search for people that they can help. Hence, as they do not rush to the exit right away, they might be spread more across the room and therefore meet less potentially opponents with which they engage in a conflict and by this lose time. The defectors are thus more likely to end up clustered at the exists and to get into more conflicts as there are more other agents. That way, their chances of getting caught in the fire might therefore be slightly increased as compared to the cooperators.

The tit-for-tat'ers are slightly less successful in evacuating, followed by the unforgiving. The unforgiving agents, initially cooperators but once having met a defecting agents, will defect until the end of the evacuation. In a new conflict, the tit-for-tat'ers copy the strategy of the agent they were in the previous conflict with. Taking into account the earlier observation that the cooperators are slightly better than the defectors, it makes sense that the tit-for-tat'ers are also slightly more successful than the unforgiving. The unforgiving agents are more likely to defect more often than tit-for-tat'ers, as they might meet a defecting agent very early in the simulation time. In general, there are more tit-for-tat'ers and more unforgiving agents in the model than cooperators and defectors. Therefore it is also more likely that some of them end up caught by the fire than the cooperators and defectors.

In about 19.75% of the scenarios, the GT-BDI model performs better than the pure BDI model. In these scenarios, the GT character distribution is given with 16.56% defectors, 14.06% cooperators, 34.06% unforgiving and 35.31% tit-for-tat'ers. It is interesting to note that this distribution is very balanced. The minimum and maximum value for the unforgiving and the tit-for-tat'ers was 10% and 20% respectively and for the cooperators and the defectors 30% and 40%. There are thus slightly more defecting agents. Due to their more selfish nature, their desire to walk around randomly turn into the desire to evacuate earlier than the more selfless nature. Thus, they start evacuating and moving towards the entrances earlier than the more selfless agents. Consequently, they are a bit faster at evacuating. However, as already noted earlier, at the same time they are more likely to end up in conflicts with other agents that also rush towards the entrances. The more selfless on the contrary, do not evacuate immediately but continue walking around the room to look for people that might need assistance. By this, they end up being more spread out in the room and therefore are less likely to encounter agents to get into conflict with and by this to lose time.

2) Implementation of Robots and Trust: To analyse the impact of having evacuation robots in the combined GT-BDI model, different sets of simulations were conducted in the parameter settings that validate the GT-BDI model. First, simulations were conducted with only stationary evacuation robots and second with robots moving around randomly. The resulting evacuation times, the success of the evacuations as well as the evolution of trust in the robots was analysed. The size of the robot fleet as well as parameters characterising the trust of humans into robots were varied to study their implication for the model results outlined in Section V-C2.

The success of evacuations depends on how many victims die in the fire that breaks out somewhere in the room. Thus, in order to successfully evacuate from the room, the victims need to avoid the fire while they rush towards the entrance they intent to exit the room from. When looking at the success of the evacuations, it is interesting to note that the difference between having no robots and having stationary robots is only marginal. However, comparing the success of evacuations with stationary robots with moving robots shows, that moving robots can lead to a slight increase in the success. At the same time, the results suggest that an increasing size of robot fleet is able to increase the success of the evacuations, but again only if the robots are moving. The moving robots are avoiding the fire and if risking to get stuck in the position of the fire, the robots move back. In the scenarios with no robots or stationary robots, this backing away from the fire is not happening. Thus, it is assumed that in the critical situations, where an agent might otherwise get stuck in the position in the fire, the evacuee perceives a robot that is moving back just in time to adjust its heading towards the nearest entrance. That way, the evacuee avoids the fire and the success of the evacuation increases. More robots thus increase the chance of having robots nearly getting stuck in the fire and thus moving back and informing evacuees that otherwise would die. Stationary robots do not having this effect as they do not move away from the fire.

Evacuation times on average are shorter with robots than without robots and benefit from high levels of trust of the agents in the robots. This is true for both stationary and moving robots: moving robots as opposed to stationary robots further decrease evacuation time. Evacuation time is measured from the moment on when the fire in the room breaks out until the last living agents has evacuated. The robots are not evacuated. When an evacuating agent sees a robot, this robot will point it towards the nearest exit. Agents that are unfamiliar with the room in which the fire breaks out will intend to evacuate through the main entrance, through which they are assumed to have entered the room. They are thus unaware of their being emergency exits that might be closer. Thus, by encountering a robot, they become aware of a closer exit and leave the room via this exit. This speeds up the individual evacuations of all agents and thus also the overall evacuation time. It is interesting to note, that moving robots speed up the evacuation more than stationary robots. In fact, as the moving robots are not strategically moving through the room (e.g., moving towards positions where there are many people clustered together) it is surprising that there is that much of a difference, with evacuation times that are halved. The stationary robots are positioned randomly across the room. At the outset of the simulation time, the agents are also randomly positioned and are walking around randomly. The chance of encountering a robot are thus everywhere equally high at the beginning of the simulation time. After the fire breaks out and the first agents start evacuating, they are moving closer towards the exits. With stationary robots, the chance of meeting a robot are still everywhere the same. With moving robots however, the chances of meeting a robot when moving towards the exits increase because the robots get stuck at the walls. When random movement of the robots makes them face a wall, it takes a couple of time steps before they adapt their heading and move away from the wall again. As a result, at given time steps, the distribution of robots in the room favors the walls and the chances of meeting a robot here are higher as well.

Trust of the agents in the robots is lower when the robots are stationary as compared to when they are moving. In both cases, the initial trustiness determines the levels of trust that are reached during the evacuation. If the trustiness is high, higher levels of trust can be reached during the simulation. In general, the values are more or less halved, which is to be expected as the low trustiness value is also the half of the high trustiness value. Lower values of trust are found when there is a small number of robots, whether they are stationary or moving. Higher levels of trust are found with more robots. This is interesting, as one could have expected the opposite: with more robots, the chances of having an unsuccessful interaction with a robot are higher and therefore, the resulting levels of trust are lower. This, as well as the difference between stationary and moving robots suggest, that encountering more robots and interacting with more robots leads to an increase in trust more often than a decrease.

3) Limitations: In the prior sections, the model results have been analysed and discussed and the model has been concluded to be valid. The model is constructed on a number of several assumptions that limit the overall validity of the model. These arise from choices that had to be made during the process of modelling as well as during assumptions made while evaluating the results.

To begin with, the fire in the model is static. It is not moving and there is no smoke propagating. This does not capture the complexity of disaster settings, where there might be smoke, fire, and debris. In the context of answering the research question that is at the heart of this study, namely to build and validate a GT-BDI model, this represents an acceptable choice. In addition, the benchmark to which it was compared does not take into account any smoke or movement of the fire neither. Hence, this limitation does not restrict the validation of the model.

Then, the character profiles of the agents range from selfless to selfish people. The selfless people are assumed to continue walking around the room randomly after the fire has started, with the aim of finding people to help. They never actually help people however. The explicit interaction between a person that needs help and a selfless person does is not modelled. However, this way of modelling the behaviour of selfless people does impact the time they need to successfully evacuate from the room. As this is what the model intents to capture, this represents a valid choice. Falling, for instance as a consequence from a conflict with an agent, is not modelled explicitly. However, in the model, a conflict has a certain duration, which can cover the time of falling and of getting up again. The conflict duration is the same for all agents, while agents with different characters might engage for shorter or longer times in conflicts. At the same time, if an agent is in a conflict, all other agent that have a relation to this agent rush towards it with the aim of helping it. This results from the assumption that people close to each other will give each other support when being impeded to evacuate as a result from a conflict with an opposing agent. There no difference in this behaviour between the selfish and the selfless, while it could be assumed that agents that are more selfish might not rush to help, even their friends or family. There is also no distinction of different types of relationships, for instance whether a group of people are friends or family. In general, it can be assumed that people might treat they family differently in an emergency situation than their friends.

Regarding trust in robots, agents are assumed to be able to tell whether or not robots are indeed faulty. This assumption is crucial to model the dynamics of trust over time. If an agent would not perceive that a robot is faulty, the affect of this unsuccessful interaction on the level of trust of this agent in robots could not be measured. At the same time, in the scenarios with moving robots, faulty robots are also able to move around the room. Here, one could assume that those that have the most sever failures might not be able to move anymore. Those could then end up being stationary robots. In addition, different agents might have different propensities to trust. In the model, all agents, no matter their background and demography, have the same trust dynamics, while these might not be independent. Also, a failed interaction with one robot affects an agent's trust in all other robots as well.

VI. Conclusion

During SaR missions, time is a crucial factor for success. In order to improve disaster response measures during indoor evacuations, a good understanding of human decision making during emergency situations in needed. As the overall behaviour of the interactions between individual evacuees is complex, computational simulation models are needed to understand how evacuation times can be reduced and success of evacuations can be improved. Existing models to simulate evacuations are not able to capture all aspects of the nature of human decision making. BDI models do not capture the strategic considerations people make and GT models do not capture the cognitive process of taking decisions. This study thus aimed at combining these two approaches to paint a fuller picture of human decision making during indoors evacuations. It was found, that indeed, adding GT to a BDI model can improve the performance of the resulting model and makes it more realistic. This depends on the exact distribution of GT character profiles in the population and the duration of GT conflicts, which remain uncertainties in the model.

Further improvements of disaster response measures are expected with ongoing breakthroughs in disaster robotics. SaR robots can considerably alleviate the task of rescue workers. Having SaR robots assist people during indoors evacuations is one of the tasks of these robots. For the presence of SaR robots to benefit the evacuation process, humans need to trust these robots. Hence, this study also aimed at modelling the presence of evacuation robots and to evaluate whether these can improve evacuation times as well as the success of the evacuations. The results suggest that SaR robots are able to reduce evacuation times. Interestingly, with an increased number of robots, the evacuation times can be reduced significantly. At the same time, an increase number of robots also leads to a significant increase of the level of trust that evacuees have in the robots. Thus, it can be concluded that if the level of trust of humans into robots could be improved, a further improvement of the evacuation times is expected.

Also, the difference in evacuation time when having stationary as opposed to moving robots is interesting to note. Moving robots were significantly improving the evacuation times, even when they were moving around the room only randomly. It is hence expected that robots that move strategically, for instance to clusters of people, can further benefit the evacuation process.

Recommendations for further research include taking a closer look at trust: [37] find, that in interactions between humans, trust is a self-fulfilling prophecy. When delegating a task to another human, the trustor shows that she trusts the trustee. This, as a result, influences the behaviour of the trustee. As the later knows and is aware of the fact that she is trusted, she will commit more to the task that she is being delegated. So far, the robots as conceptualized for the evacuation model are very simple and will not be aware of being trusted. To take account of this, a behavioural model will need to be included in the model of the robots to account for this. In addition, the appearance of the robots also play a role in trust: People place more qualities into robots that look more anthropomorphic. They are less inclined to anthropomorphise when robots make mistakes [12]. For now, the exact appearance and how this impacts the trust of the agents into the robots it not taken into account and can be included by modelling robots of different shapes and attributing a different trust dynamics to each. Also, the relation between people's demographic and their trust dynamics in robots could be further analysed and implemented in the model. Potentially, people with different background have different propensities to trust robots and different rates of decreasing and recovering trust in robots after failed interactions. At the same time, a solid model of the trust dynamics is needed. The levels of trust resulting from running the simulations do not really depend on the trust parameters that model the trust dynamics. This observation suggests, that some more work is needed in this regard, in order to make an abstract concept such as trust quantifiable and be able to accurately model it.

Regarding the modelling of human behavior, further aspects can be added to the GT-BDI model. In terms of the implementation of GT, in their model, [32] vary the conflict cost in function of an opponent's size. Thus, when in a conflict with an opponent that is considerably larger, the agent is more likely to lose and the conflict cost will be greater than in a conflict with a smaller agent. This has not been implemented in this model, as agent size has not been modelled. In the BDI model of [4], other elements of evacuations were also implemented, namely falling and helping behaviour of agents. These have not been implemented in this model as the conflicts and the conflict durations of the GT conflicts are seen as overlapping. To implement helping behaviour in the GT-BDI model of this study, additional GT rules could be derived and would need to be distinguished from the implemented GT rules.

Finally, the model of the implemented robots is simplistic: These are either stationary or move randomly through the evacuation setting. Here, a more sophisticated model of the robots could have them anticipate how the victims will move and then adapt to where clusters of evacuees might end up. That way, the evacuation robots could better assist the victims and potentially decrease evacuation time.

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Part III

Discussion: Conclusion & Recommendations

7 Conclusion & Recommendations

The goal of this research is to address the research objective formulated in section 2. This section recapitulates the major findings of the previous sections and proposes some conclusions as well as some recommendations for future research.

7.1 Conclusion

The research objective of this thesis was to create a simulation model of an indoor evacuation scenario that captures human behavior in the presence of SaR robots. The main research question of this thesis is: *How can human behavior during an indoor evacuation scenario be modelled in a simulation model in order to understand the dynamics of human decision making, with and without the presence of SaR robots potentially influencing human behavior?*

To put it in a nutshell, this study found that integrating GT into a BDI model indeed can enhance the model's performance and realism when comparing it to existing benchmarks. However, uncertainties regarding the distribution of GT character profiles in the population and the duration of GT conflicts remain in the model and affect its performance. Moreover, the presence of SaR does influence human behavior in that they are able to accelerate the evacuation process. A difference in these results was found between stationary and moving robots, where the latter can speed up the evacuation process even more. The gains in evacuation time depend on the number of present robots and the level of trust of the agents in the robots.

Several sub research questions were formulated to help answering the main research question. In the following, the answers to these are summarised separately.

7.1.1 The Role of Robots in SaR Missions

One of the major challenges in disaster management is a disaster response. SaR missions are a crucial component of these, and are carried out in hazardous environments that endanger the lives of first responders and rescue workers. To mitigate risks, the deployment of a fleet of robots is considered a promising solution. However, robots themselves encounter difficulties, including limited sensory capabilities and the challenging task of locating and tracking trapped victims. Developing a model that captures victim behavior can provide valuable insights into their whereabouts and assist in improving SaR missions. In the context of indoor evacuations, a model of human decision making, that is able to estimate human behavior in the presence of evacuation robots can lead to an efficient mission planning of SaR operations.

7.1.2 Modelling Human Decision Making in Evacuation Scenarios

Computational simulation models are necessary to evaluate how evacuation times can be minimized and the success of evacuations can be improved. However, existing models fail to capture all aspects of human decision making. BDI models do not account for strategic considerations, while game theory models overlook the cognitive processes involved in decision-making. The GT-BDI model combines these two approaches to provide a more comprehensive understanding of human decision making during indoor evacuations. The study found that integrating GT into a BDI model indeed enhances the model's performance and realism when comparing it to the chosen benchmarks, depending on the distribution of GT character profiles in the population of agents and the duration of GT conflicts.

7.1.3 Human Evacuation Behavior in the Presence of SaR Robots

Before implementing SaR robots in the model, those factors influencing human robot interaction were discovered. It was found that, to optimize the effectiveness of SaR robots, it is essential for humans to trust them. Trust is a dynamic concept that depends not only on a personal propensity to trust of a human, but also on the perceived success of interaction with a robot. Thus, trust can decrease and recover with differing rates. The results of adding robots to the indoor evacuation scenario indicate, that evacuation robots can indeed reduce evacuation times, with a significant decrease observed as the number of robots increases. The reduction in evacuation time depends not only on the number of robots but also on the level of trust of the agents in the robots. This suggests, that improving the level of trust in robots could further enhance evacuation times. Additionally, the study shows a difference in evacuation times between stationary and moving robots. Even randomly moving robots show improved evacuation times, suggesting that strategically moving robots, such as those approaching clusters of people, can provide further benefits to the evacuation process.

7.2 Recommendations for further Research

While attempting to answer the research question that is at heart of this study, some other questions were raised. Some of these arise from limitations and assumptions of the used methodology and others are recommendations for the future.

There are several potential improvements that can be made to the GT-BDI model when it comes to modeling human behavior. One aspect that could be incorporated is the variation of conflict cost based on the size of an opponent, as demonstrated in the model by Ibrahim et al. (2019). When facing a considerably larger opponent, an agent is more likely to lose, resulting in a higher conflict cost compared to a conflict with a smaller agent. The current GT-BDI model does not account for agent size. In addition, the BDI model developed by Van der Wal et al. (2017) includes elements such as falling and helping behavior during evacuations. These elements, however, have not been integrated into the GT-BDI model, as the conflicts in the GT model are perceived as overlapping. To introduce helping behavior in the GT-BDI model, additional GT rules would need to be derived and clearly distinguished from the existing GT rules.

Furthermore, research is needed into modelling the concept of trust. Amigoni et al. (2009) discovered that trust in human interactions is a self-fulfilling prophecy. When one person delegates a task to another, the trustor's display of trust influences the behavior of the trustee. The trustee, aware of being trusted, becomes more committed to the delegated task. However, the current conceptualization of the evacuation model's robots lacks the awareness of trust. To address this, a behavioral model must be incorporated into the robot model to account for trust dynamics. Furthermore, the current model of the implemented robots in the evacuation scenario is relatively simplistic. These robots either remain stationary or move randomly throughout the evacuation area. A more advanced robot model could anticipate the movements of victims and adapt accordingly, specifically identifying clusters of evacuees to provide better assistance and by this, increasing trust and reducing evacuation times.

Additionally, the appearance of the robots plays a significant role in trust. Research by **?** indicates that people attribute more qualities to robots that have a more anthropomorphic appearance. Moreover, people are less likely to anthropomorphize robots when they make mistakes. Presently, the evacuation model does not consider the specific appearance of robots or its impact on trust dynamics. By modeling robots with diverse shapes and assigning different trust dynamics to each, this aspect can be integrated. Furthermore, exploring the relationship between people's demographics and their trust dynamics in robots would be valuable. Different backgrounds may influence individuals' propensities to trust robots and their rates of decreasing and recovering trust after failed interactions. A more robust model of trust dynamics is necessary. Currently, the results for the levels of trust do not depend significantly on the trust parameters that model trust dynamics. This highlights the need for further research into quantifying trust in order to enable its accurate modeling.

Part IV

Appendix

A Testing Trust

The implementation of the interaction between agents and robots in the model depends on the level of trust of the agents in the robots. It was found in literature, that trust is a dynamic concept that decreases after perceived unsuccessful interactions and recovers after some time. This trust dynamics is implemented in the model. The model results show, that the evacuation times can be decreased by the presence of a given number of robots. They also suggest, that the higher the level of trust of agents in robots, the faster the evacuation process. The level of trust in turn mostly depends on the initial trustiness of agents in evacuation robots. According to the trust dynamics, the level of trust should also depend on success of interactions between agents and robots. However, no relationship can be observed between the parameters of trust decrease and trust recovery on the resulting level of trust, neither with stationary nor with moving robots, as can be seen in Figure 16, Figure 19, Figure 18 and Figure 19.

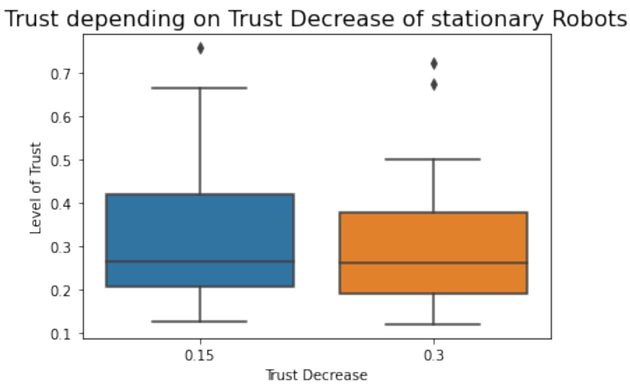

Figure 16: Levels of trust depending on trust decrease with stationary robots

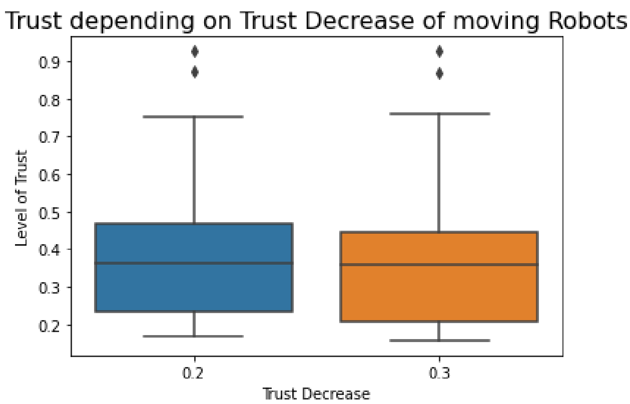

Figure 17: Levels of trust depending on trust decrease with moving robots

Therefore, the trusting parameters have been tuned to higher, extreme values to see if an effect on the level of trust can be seen in these cases. As can be seen in Figure 20 and Figure 21, the influence is still very small. However, it can be seen that an extremely low trust decrease of 0.1 leads to an average level of trust of 0.37 and an extremely high trust decrease of 1 to 0.31. An extremely low trust recovery of 0.1 leads to an average level of trust of 0.32 and an extremely high trust recovery of 1 to

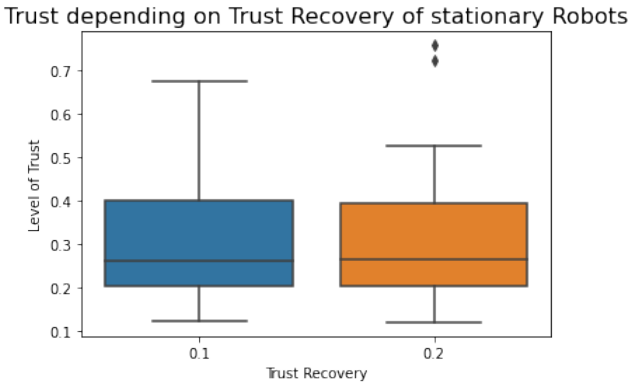

Figure 18: Levels of trust depending on trust recovery with stationary robots

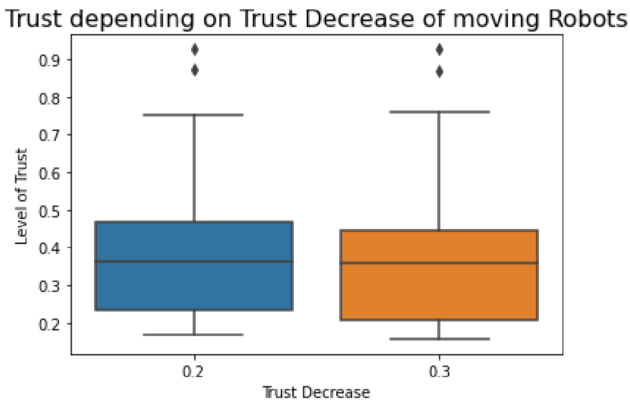

Figure 19: Levels of trust depending on trust recovery with moving robots

0.36 (see Table 4. Thus, there are marginal differences that can be seen. Those extreme values seem very unrealistic, however, and therefore have not been implemented in the analysis of the mode. Still, these observations reinforce the suggestion to further look into modelling the trust dynamics.

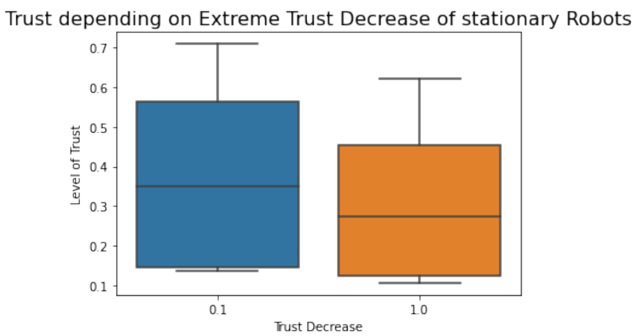

Figure 20: Levels of trust depending on extreme trust decrease values with stationary robots

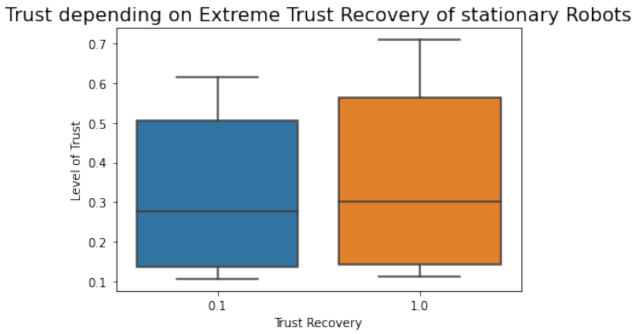

Figure 21: Levels of trust depending on extreme trust recovery values with stationary robots

Table 4: Extreme trust values and level of trust

	Level of Trust
Low Trust Decrease	0.37
Low Trust Recovery	0.32
High Trust Decrease	0.31
High Trust Recovery	0.36

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