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RESEARCH ARTICLE

GT-BDI Model: A Combined Game-Theoretic and BDI-Based Computational Model for Emergency Evacuation With Search and Rescue Robots

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ABSTRACT The catastrophic impact of disasters on affected populations necessitates effective management practices to minimize the societal and economical damages caused by disasters. This pertains planning effective measures to find and rescue trapped victims in time. Search and rescue in general is very challenging, as the number of the trapped victims may be unknown and their behaviour while trying to evacuate the disaster area is prone to variations, depending on their individual cognition and social interactions. Evacuation robots have attracted attention for their role in assisting search and rescue teams to locate and save victims. A behavioural model of the victims can provide insights for both the staff and the robots in search and rescue missions on how the trapped victims act during an evacuation, and to plan the search and rescue mission accordingly. Such a model, after being validated, can also be used for analysis of the influence of the robots in search and rescue missions. This paper proposes a novel evacuation model that integrates game theory and the belief-desire-intention (BDI) framework, in order to incorporate both the interactions of the trapped victims and their cognitive processes at the individual level. The model is validated using existing benchmark models for evacuation behaviour. Furthermore, the validated model is used to assess the effectiveness of the evacuation robots within the evacuation procedure. It is found that the presence of evacuation robots does reduce the evacuation time, as a function of the trust of the victims in these robots.

INDEX TERMS Belief-desire-intention (BDI) model, game theory, human behavior during evacuation, search and rescue robots, trust in human-robot interaction.

I. INTRODUCTION

Search and rescue is a crucial stage of early disaster response: Rescue workers need to secure the site of the disaster, locate the trapped victims, and rescue them from potential risks. A common decisive factor for the success of search and rescue missions is how fast the rescue workers can conduct search and rescue missions [1], [2]. With technological advancements in various relevant fields, such as in robotics, sensoric, and autonomy, the field of search and rescue robotics has emerged [3], [4], [5], [6], [7]. Search and rescue robots can alleviate the task of rescue workers and support them in both finding the victims and saving them from the disaster scene. Robots have proven to be very effective in such tasks for various reasons: Robots are expendable, thus can take over tasks that are hazardous for human rescue workers; robots usually have access to areas that are inaccessible or not passable for humans; and, depending on the level of their autonomy, robots are able to take effective decisions at a much higher speed than humans do [1], [8]. Disaster scenarios are highly complex, since the environment is usually very dynamic, and people act and interact with each other in various ways in order to reach the exits or safe areas. In fact, the behaviour of the trapped victims can further

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increase the tragedy of disasters [9], [10]. A recent example included a soccer game stampede in Indonesia, where around 125 people died, while trying to evacuate the stadium [11].

A computational evacuation model that allows to understand how humans act and interact with each other during an evacuation process plays a crucial role in efficiently planning search and rescue missions and in increasing the speed and success rate of evacuation processes [12], [13]. For instance, the organisers of an event may use such a model to assess how people may move in their venue in case of a disaster. This information helps the organisers to take essential preventive measures, and to evaluate whether or not the deployment of search and rescue robots will result in a more safe and fast evacuation. Furthermore, such a model — after being validated — can perform as a suitable test-bed to evaluate in advance the effectiveness of different search and rescue robotic missions (e.g., for algorithms presented in [14], [15], and [16]).

Depending on their individual goals, different people hold different intentions and thus, act differently while evacuating a disaster scene. More specifically, some people are willing to cooperate with others, while others focus on saving themselves [9], [17]. Therefore, incorporating the intentions of the trapped victims, at both the group level and the individual level, is crucial for precisely predicting their actions during an evacuation.

This paper is structured as follows. The main motivation and contributions are given in Section II. Relevant background discussions about modelling the evacuation behaviour of humans, as well as the use of search and rescue robots, in particular evacuation robots, is given in Section III. Section IV explains the frameworks that together develop the GT-BDI model, representing the actions and interactions of the trapped victims during an evacuation process. A case study is performed in Section V for validating the GT-BDI model with respect to the state-of-the-art benchmarks. The validated model is then used in computational simulations to analyse the influence of robots in search and rescue missions, especially as a function of the trust level that humans develop in these robots. Section VI recapitulates the paper and proposes topics for future research.

II. MOTIVATION AND MAIN CONTRIBUTIONS

This paper combines game theory and the belief-desire-intention (BDI) framework, in order to develop a simulation model for understanding and predicting the behaviour of the trapped victims during an evacuation process. The model is further used to evaluate the effectiveness of evacuation robots for improving the speed and safety of evacuation processes, taking into account the varying dynamics of the trust of victims in these robots.

The existing models for indoor evacuation scenarios mainly use separate frameworks (at the individual and group levels) to model the decision making of humans in multi-actor settings [18]. In other words, these models cover either a macroscopic or a microscopic framework. Integrating game theoretic concepts with the BDI framework for modelling an indoor evacuation, however, allows to combine the best of these two points-of-view: BDI models [19], [20], on the one hand, are able to capture the cognitive processes involved in the human decision making. However, they do not necessarily capture the strategic decision making of humans, especially when they have to make trade-offs regarding their own and others' safety. Game theory [21], on the other hand, captures such strategic considerations, whereas it describes all the interactions of humans, through making trade-offs that aim at maximising one's own utility. This point-of-view, however, lacks all other dimensions of human interaction (e.g., when one sacrifices their own utility to save the life of a child), which BDI does capture.

So far, no evacuation model has incorporated human-robot interactions in the context of employing search and rescue or evacuation robots. However, the presence of evacuation robots influences the behaviour of the trapped victims [22], [23], [24], and thus the chances of success of the evacuation process. In addition, while research has been conducted on the trust of humans in automation and specifically in robots, no implementation of such a model in evacuation processes in the presence of evacuation robots exists.

The main contributions of this paper include:

- Proposing a novel integrated model, called GT-BDI, based on mathematical modelling of both the individual and social behaviour of humans in emergency evacuation processes, by integrating game theory and the belief-desire-intention framework
- Incorporating human-robot interactions into the model, particularly by proposing a dynamic equation for modelling the evolution of the trust of the victims in the robots and the impact of this trust on the human-robot interactions and thus, on the outcomes of the evacuation process
- Validating GT-BDI via extensive simulations in NetLogo, compared to two benchmark models, and using the validated model for an extensive analysis of the impacts of including robots with varying conditions (e.g., stationary, non-stationary, perfectly functioning, partially faulty) within evacuation processes on the success rates and speed of the evacuation

III. BACKGROUND

This section covers a background discussion on the key elements relevant for the paper. In particular, we discuss the state-of-the-art of evacuation modelling, the challenges of evacuation processes for evacuation robots, and the dynamics of trust (especially in human-robot interactions), which influences the evacuation behaviour of the trapped victims.

A. EVACUATION MODELLING

An evacuation scenario can be considered as a multi-agent system, with each agent representing a victim. The overall evacuation behaviour emerges from the interactions of these agents who at the individual level in general possess different behaviours from one another. These interactions at the individual and group levels are too complex to be described via mathematical models. Instead, computational models that incorporate mathematical formulations for the dynamics of the actions and interactions of the agents are excellent options.

1) DETAIL LEVEL OF EVACUATION MODELS

Computational evacuation models can be divided into macroscopic, microscopic, and mesoscopic [25].

Macroscopic models describe the overall behaviour of the agents using mechanics of continuous media. Such models are, for instance, based on fluid dynamics principles [26] and lattice gas approaches [27]. Macroscopic models do not incorporate the interactions of the agents, thus they are not always ideal for precise modelling of evacuation processes with significant variations in the behaviour and characteristics of the involved agents.

Microscopic models represent the interactions of the agents at the individual level. Thus, unlike macroscopic models, microscopic models analyse how an overall group behaviour emerges from the individual interactions. Microscopic models are often implemented using agent-based modelling, which provides a computational framework for representing the dynamics of geo-spatial systems, i.e., systems that change in time and in space [28], [29], [30]. Examples of microscopic evacuation models are given in [17], [31], [32], [33], [34].

Mesoscopic models bridge macroscopic and microscopic points-of-view, where the agents are clustered into groups of (almost) similar behaviour. A main advantage of mesoscopic models compared to microscopic ones is their lower computational burden. Moreover, in evacuation scenarios, people indeed form groups–e.g., with friends, family members, colleagues–and are more likely to help members of their own group while evacuating a disaster scene [35], [36], [37]. Thus, mesoscopic frameworks are ideal for modelling the evacuation behaviour of victims.

Social force models [38] and cellular automata models [39], [40] form two categories of evacuation models that are widely used. Social force models represent the dynamics of the movements of people by considering each person as a particle that moves subject to virtual driving, repulsive, and attraction forces, e.g., adhering to social norms, attraction to exits or other desired destinations, repulsion by objects or people that may collide with the person. While similarly to microscopic models, social force models include the individual behaviour of people in the modelling, the interactions among the people are rather simplified, as aggregate virtual forces are considered that steer the evacuation behaviour of the individual person. Thus, such models may be categorised as mesoscopic. Cellular automaton is a common framework for microscopic modelling of the evacuation behaviour of humans. Cellular automaton simulates the environment as a grid, where each cell may be occupied by maximum one person. The dynamics of the motion of people is determined by rules that are based on the states or attractiveness of the neighbouring cells.

2) STATE-OF-THE-ART APPROACHES

Game theory and the BDI framework have been used separately for agent-based evacuation modelling [17], [34], [41], [42], [43], [44], [45], [46], [47]. Game theory mathematically represents strategic interactions of agents [21], [28], [48]. A game represents different strategies for achieving specific outcomes, based on the values that the players associate to these outcomes. Players include all those agents that are engaged in the decision making. Each player is assumed to possess a bounded rationality, tries to maximise a certain utility, and has a set of actions. The sequence of these actions in an iterative game (i.e., with multiple rounds) determines the player's strategy, which is selected based on an anticipation of the actions of other players. The outcome of the game is determined based on the strategies of all players. Different players may generally prefer different outcomes. Each player assigns a value, called the player's utility, to each outcome. The game is subject to rules, which limit the set of possible actions that a player can take.

For modelling the evacuation behaviour of humans in emergencies, state-of-the-art pedestrian dynamic models (including social force models and cellular automata) and game theory offer complementary perspectives: Social force and cellular automaton models provide insights into the impact of physical and social interactions of humans on their movements, whereas game theory allows to understand strategic interactions of people, i.e., decisions and actions that impact one another, a concept that is highly relevant in emergency evacuations.

A main criticism towards game theory concerns its reliance on the rationality of agents, whereas in emergency evacuations this assumption is rather invalid. Thus, in this paper we propose to integrate game theory with the BDI framework in order to model differences of cognition and decision making of the agents and to relax the assumption of their rationality.

The BDI framework is a simplified representation of the decision making of humans, who are considered as agents that possess the following features: beliefs about the state of the world, where these beliefs can change and new beliefs can be developed in time; desires, which reflect the drives and preferred situations for the agent; intentions, which reflect what an agent has chosen to do and thus the desires to which the agent has committed [19], [49], [50], [51]. Due to its adaptability and properly mimicking the cognitive processes of humans, BDI is an interesting and powerful framework for modelling the evacuation behaviour of humans. In particular, BDI can be integrated with other pedestrian dynamic models, e.g., social force models and cellular automata, to relax the assumption that all agents exhibit homogeneous properties and to enhance the precision, realism, and adaptability to real-world dynamics of the model. To be more specific, in combination with a social force model, BDI will influence the magnitude and/or direction of the drive, attraction, and repulsive forces. When integrated with a cellular automaton model, the rules that steer the transition of the agents from one cell to another will be tuned according to the BDI rules.

The BDI model has been used for modelling evacuation behaviour of people in emergencies: BEN (Behaviour with Emotions and Norms) [31] is a BDI model that associates emotions (based on the personality, social relationships, emotional contagion) and norms (based on the laws and obligations) to the evacuation behaviour of agents. IMPACT [17] also uses the BDI framework to model socio-cultural, cognitive, and emotional factors that influence the evacuation behaviour of people.

B. ROBOTS IN EVACUATION

While robots are used for different purposes in search and rescue, we focus on evacuation robots used for evacuation, i.e., robots that assist the trapped victims to evacuate a disaster scene by guiding them to safe areas and towards the exits. Several factors play a role in the level of effectiveness of evacuation robots: First, since the number and position of the trapped victims inside a building are usually unknown, robots should locate the victims. Potential movements of the victims make localisation even more complicated for robots [52], [53]. The speed of localising the victims is a key factor in the effectiveness of evacuation robots. Second, after detecting the victims, evacuation robots should track and guide them [54], [55]. Thus, whether or not a robot can stay with a victim until the victim safely evacuates the building is another determining factor for the effectiveness of evacuation robots. Third, evacuation robots should decide about task allocation plans among themselves [12]. Whether or not the task allocation is optimal impacts the outcome of the evacuation. Finally, the evacuees should have trust in evacuation robots to collaborate with and follow their advice [56]. Whether or not trust is developed and sustained determines the level of effectiveness of evacuation robots.

C. TRUST DYNAMICS

On the one hand, humans generally have a tendency to trust robots less, when these robots show a high autonomy and a low transparency [56]. On the other hand, research shows that — especially in emergency situations — people tend to over-trust robots, even when these robots do not function as expected (e.g., when these robots fail to find the shortest or safest path to the exits [56], [57]).

Trust is a psychological attitude, based on the beliefs and expectations of a person about the trustworthiness of a potential trustee, in helping that person to achieve their goal, e.g., to safely evacuate a disaster scene [56], [58]. Trust is an important factor in human-machine interactions. Research shows that in most situations when humans interact with a robot that is faulty or that makes mistakes, their trust in the robot decreases rapidly [59]. Moreover, the robot appearance has shown to impact the trust of humans in the robot [60].

Trust, in general, is a dynamic variable, which evolves through three phases [61], [62]: (a) trust formation, (b) trust dissolution, (c) trust restoration. More specifically, trust is developed and is potentially increased over time based on the predictability of the trustee's behaviour. In case trust violation occurs, trust decreases with a high rate. Finally, at some point trust may start to be recovered (although not necessarily to the same level that it originally was). Failure of a robot to sustain the trust of humans may be categorised as acute and chronic [58]. With acute failures, the trust dissolution stage is transient, i.e., trust is recovered after a maintenance or a repair is performed to the robot. Chronic failures, however, represent a permanent decline in the trust.

An analysis of how trust varies in time reveals that the dynamics of trust can properly be modelled via a first-order differential equation. In other words, a failure changes the trust in time according to an exponential function [58]. Moreover, research shows that the speed of the decrease in trust is higher than the speed of its recovery [63]. While incorporating all these effects, first-order difference equations for trust dynamics offer simplicity, computational efficiency, and the ability to capture gradual trust evolution, making it a widely used approach in the literature.

Next section explains the details of the proposed evacuation model, which combines game theory and BDI.

IV. PROPOSED INTEGRATED MODEL: GT-BDI

In order to analyse the complex dynamics of an evacuation process and to estimate the effectiveness of deploying evacuation robots, extensive analysis based on a reliable behavioural model is needed. Such a model should incorporate various decisions made at the individual level impacted by the cognition of a person, strategic decision making of humans when involved in a conflict, as well as the dynamics of human-robot interactions. A mathematical or computational model that possesses all these characteristics is currently missing. We fill in this gap by proposing an indoor evacuation model that, considering a discrete-time computational setting, integrates game theory (for representing the strategic interactions of victims during conflicts), the BDI framework (for representing the individual decision making processes), and human-robot interactions impacted by the dynamics of trust of the victims in robots.

The rules that determine how the agents interact with their environment and with other agents in GT-BDI, as well as the characteristics of the agents are explained first. We then include additional agents representing the evacuation robots in GT-BDI. These robots influence the dynamics of the interactions and decision making of the victims by governing the dynamics of the trust of victims in robots trough their performance in the human-robot interactions.

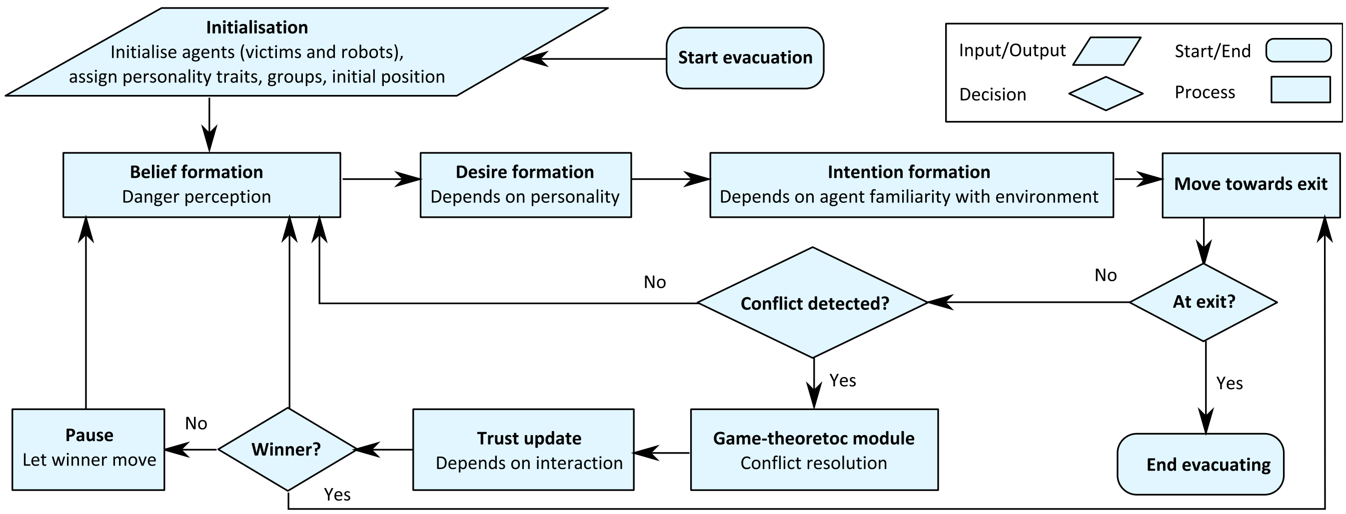

FIGURE 1. **Flowchart representing the logic behind the GT-BDI model.**

In fact, depending on the outcome of the previous interactions with the robots, victims may lose or gain some trust in the evacuation robots.

Similarly to [17], the population of the victims in GT-BDI is categorised into children, adults, and elderly, with different speeds and familiarity with the environment. Moreover, for the victims we consider one of the following four different personalities, ranging from very selfless to very selfish: the altruists, the selfless, the egoists, and the selfish. The selfish act only in the advantage of their own evacuation, whereas altruists are at the other end of the spectrum, caring about others. The selfless first act like the altruists, but then mimic the strategy of the last agent they have been in conflict with. The egoists start like the altruists but turn into selfish after getting involved in a conflict with a selfish agent. These personality traits affect the desires of the agents in the BDI framework, thus their individual decision making, and determines which game-theoretic strategies an agent will take when in a conflict with other agents.

Agents that have a relationship with each other (e.g., family members, colleagues, friends) form a group. Agents in a group are assumed to move together during the evacuation process.

A. BDI FRAMEWORK FOR EVACUATION BEHAVIOUR

According to [64], the psychological and emotional factors that affect the collective behaviour of crowds remain a challenge for many models. By using the BDI framework, the process of making and executing a plan via humans can be modelled, taking into account such psychological and emotional factors. The main concepts of the BDI framework, i.e., the beliefs, desires, and intentions of the agents, are modelled in GT-BDI as it is explained next.

1) BELIEFS

Agents develop a belief about whether or not a situation is dangerous, based on both their own feeling and their perception about how other agents feel about the situation. This represents the concept of social contagion [17].

2) DESIRES

An agent's desire may be to continue walking around randomly or to exit the danger zone. This depends on both the belief of the agent about the degree of danger and the agent's personality. The altruist and selfless agents will in general walk around for longer, to assist other agents. The selfish and egoist agents, however, prefer to exit the danger zone as soon as possible in order to save themselves. Moreover, independent of their personalities, agents that are in the same group desire to remain together.

3) INTENTIONS

When the desire of an agent is to exit the danger zone, its intention will be to get as soon as possible to its nearest exit. Whether or not an agent knows where the nearest exit is, depends on the familiarity of the agent with the environment defined by a binary time-dependent variable $\beta_i(k)$ for agent i at time step k. An agent that is not familiar with its environment at time step k (i.e., $\beta_i(k) = 0$) only knows about the main entrance that it has used to enter the building. Thus, its intention will be to reach this main entrance. When an agent gets involved in a conflict, the intention of its group members who have the desire to stay together will become getting to the conflict scene.

B. NON-COOPERATIVE GAME THEORY FOR EVACUATION BEHAVIOUR

Game-theoretic interactions are divided into cooperative and non-cooperative. Cooperative game theory analyses possible coalitions among the players. This cooperation may be externally enforced, by establishing which players should cooperate and how much each player should sacrifice for the common interest of the coalition [65]. In non-cooperative game theory, however, there is either no coalition or if any

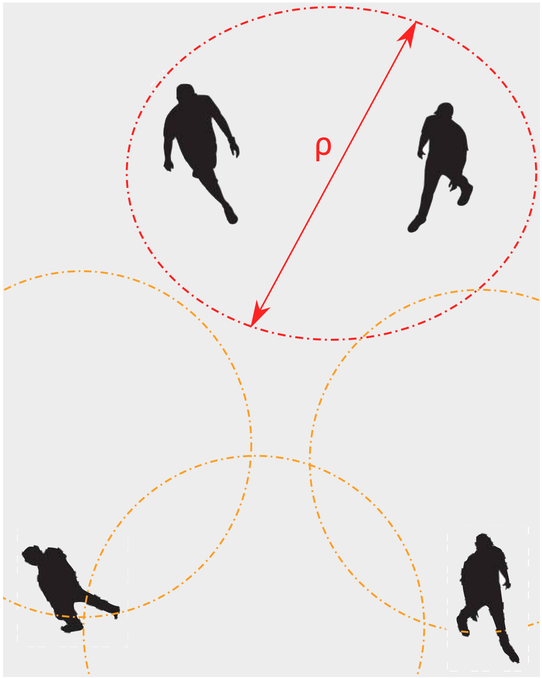

FIGURE 2. A conflict occurs and a game is launched whenever at least two agents are in a close neighbourhood of each other (e.g., in a distance equal to or smaller than a given threshold ρ). The two agents on top of the figure face a conflict, whereas other agents are outside of the conflict zones of each other.

agreements are made among the players, these should be self-enforcing and a result of the interactions of the players. With non-cooperative games only the individual strategy and utility of the players are considered. Thus, non-cooperative game theory is the most natural choice for modelling the emerging evacuation behaviour of humans in a disaster setting. We propose a non-cooperative game theory approach inspired by the methods in [41] and explain it next.

In the evacuation process, a game is launched whenever a conflict arises between at least two agents, i.e., when the distance of these agents is smaller than or equal to a given threshold ρ (see Figure 2). When a conflict arises between agents, they should decide who will first take the next step. For this, the players have two options, depending on their personalities: cooperation or fighting. Each of these options results in different utilities for the agents. After resolving the conflict, the winning agent gets priority to move forward.

Next, we explain the mathematical formulation of the game theory module of GT-BDI. Note that all mathematical notations together with their definition are presented in Table 1 in order of their appearance in the text. Additionally, the definition/explanation for all the notations has once more been given right after their first appearance in the text.

Suppose that agent i and agent j are in a conflict at time step k. This implies that the distance between these agents is equal to or smaller than ρ (see Figure 2). Thus, we have:

$$\left\|\boldsymbol{r}_i(k) - \boldsymbol{r}_j(k)\right\| \leq \rho \tag{1}$$

with $\boldsymbol{r}_i(k)$ and $\boldsymbol{r}_j(k)$ the coordinates for the position of, respectively, agent i and agent j at time step k, and $\|\cdot\|$ representing the norm function, which is used to estimate the distance of the two agents in (1). A conflict between agents i and j implies that $j \in \mathcal{C}_i(k)$ or equivalently $i \in \mathcal{C}_j(k)$, where $\mathcal{C}_i(k)$ is a set that includes the indices of all those agents that are involved in a conflict with agent i at time step k. Since the ultimate aim of each agent is to reach the closest exit as soon as possible, we first estimate the evacuation time $T_i^{\text{evac}}(k)$ of each agent i via the following relationship:

$$T_i^{\text{evac}}(k) = \frac{d_i(k)}{v_i(k)} \tag{2}$$

which is estimated based on the distance $d_i(k)$ of agent i at time step k from its nearest exit and its speed $v_i(k)$ estimated for the same time step. Note that this approximation (which is updated regularly as the distance and speed of the agent vary in time) is simply based on the assumption of uniform motion of the agent.

Suppose that the coordinates of exit e (with e an index that specifies each exit, where n^{exit} number of exits are present in the building) and the coordinates of the main entrance of the building are, respectively, $\boldsymbol{r}_e^{\text{exit}}$ and $\boldsymbol{r}^{\text{enter}}$. The distance $d_i(k)$ used in (2) is then determined by:

$$d_i(k) = \begin{cases} \displaystyle\min_{e=1,\ldots,n^{\text{exit}}} \left\|\boldsymbol{r}_e^{\text{exit}} - \boldsymbol{r}_i(k)\right\| & \text{If } \beta_i(k) = 1 \\ \left\|\boldsymbol{r}^{\text{enter}} - \boldsymbol{r}_i(k)\right\| & \text{If } \beta_i(k) = 0 \end{cases} \tag{3}$$

The rationale behind (3) is the following: In case the agent is familiar with its environment at time step k (i.e., $\beta_i(k) = 1$), it then knows the coordinates for the position $\boldsymbol{r}_e^{\text{exit}}$ of all exits $e = 1, \ldots, n^{\text{exit}}$ and thus, is able to find the nearest exit, which has the least distance from the position $\boldsymbol{r}_i(k)$ of the agent. Otherwise, when the agent is unfamiliar with its environment (i.e., $\beta_i(k) = 0$), it is only aware of the coordinates of the position of the main entrance, through which the agent has entered the building. Thus, the distance estimated by the agent from the exit is based on the position $\boldsymbol{r}^{\text{enter}}$ of this main entrance.

In (2), the magnitude $v_i(k)$ of the speed estimated at time step k for agent i is computed via:

$$v_i(k) = \min\left\{\frac{\displaystyle\sum_{\ell \in \left(\mathcal{C}_i^{\text{eff}}(k) \cup \{i\}\right)} v_\ell^{\text{nc}}(k)}{\left|\mathcal{C}_i^{\text{eff}}(k)\right| + 1}, v_i^{\text{nc}}(k)\right\} \tag{4}$$

$$\mathcal{C}_i^{\text{eff}}(k) = \begin{cases} \mathcal{C}_i(k), & |\mathcal{C}_i(k)| \geq N^{\text{compact}} \\ \emptyset, & |\mathcal{C}_i(k)| < N^{\text{compact}} \end{cases} \tag{5}$$

with $v_\ell^{\text{nc}}(k)$ the speed of agent ℓ if it would not be involved in a conflict at time step k, and $|\cdot|$ used for the set cardinality. In fact, (4) is based on the assumption that all agents $\ell \in \mathcal{C}_i(k)$

TABLE 1. Mathematical notations of the paper.

Notation	Definition
	Mathematical notations used in Section IV-B, Equations (1)–(8)
k	Discrete time step
T	Sampling time of the discretisation
e	Index variable for the exits of the building
n^{exit}	Total number of exits in the building
ρ	Upper distance threshold, where for this or smaller distance values a conflict will occur among agents
T^{lost}	Lost time, i.e., the delay that occurs for agents when they need to recover from the consequences (e.g., falling or being harmed/injured) of physical confrontations in a conflict
$\\|\cdot\\|$	Norm function
$\|\cdot\|$	Cardinality of a set
$\mathcal{C}_i(k)$	Conflict index set for agent i at time step k, i.e., a set including the indices of all agents that are in a conflict with agent i at time step k
N^{compact}	A threshold for the number of agents in conflict that determines how compact the population in conflict is
$\mathcal{C}_i^{\text{eff}}(k)$	Effective conflict index set for agent i at time step k that is empty if according to the threshold N^{compact} the agents in conflict are not compactly populated and is the same as $\mathcal{C}_i(k)$ otherwise
$v_i^{\max}(k)$	Maximum speed that agent i would move with at time step k, if the space in front of it was conflict-free (we consider two cases, i.e., a maximum walking speed and a maximum running speed, per agent)
$v_i^{\text{nc}}(k)$	Magnitude of the speed of agent i at time step k assuming that the agent will experience no conflicts at this time step, where this speed may be $v_i^{\max}(k)$ or a value less than $v_i^{\max}(k)$ if the agent is recovering from a former conflict
$v_i(k)$	Magnitude of the actual speed of agent i at time step k when the agent may or may not be involved in a conflict, where this speed may be equal to $v_i^{\max}(k)$, or $v_i^{\text{nc}}(k)$, or any other value smaller than $v_i^{\max}(k)$ depending on the nature of the scenario the agent experiences at time step k
$\beta_i(k)$	Familiarity (a binary variable) of agent i with the building at time step k
$\boldsymbol{r}_i(k)$	Coordinates of agent i at time step k
$\boldsymbol{r}_e^{\text{exit}}$	Coordinates of exit e of the building
$\boldsymbol{r}^{\text{enter}}$	Coordinates of the main entrance of the building
$T_i^{\text{evac}}(k)$	Evacuation time of agent i estimated at time step k
$d_i(k)$	Distance of agent i to the exit it chooses (based on its familiarity with the building) at time step k to use for evacuating the building
$\Delta u_i(k)$	Utility increment for agent i at time step k
$c_i(k)$	The cost for agent i after resolving its conflict at time step k
	Mathematical notations used in Section IV-C
$\tau_i(k)$	Level of trust of agent i in evacuation robots at time step k
δ_i	A fixed rate for the decrease of the trust of agent i, when interacting with a robot that shows a failure in class 1 (i.e., the least severe class of failures)
$\sigma(k)$	A negative integer factor that scales up the decline in the trust at time step k, when interaction at this time step is with a robot that exhibits failures of classes higher than 1
$\tau_i^{\max}$	Propensity of agent i to trusting a robot

that are in conflict with agent i at time step k and agent i itself intend to adopt the same speed when they are very close to each other, i.e., in a distance equal to or smaller than ρ, and when their number exceeds a given positive threshold N^{compact} that determines how compact the population in conflict is. This is why in (5) an effective conflict index set $\mathcal{C}_i^{\text{eff}}(k)$ has been defined that is the same as $\mathcal{C}_i(k)$ in case the population in conflict is considered compact, and else is empty. Then, based on (4) the average of the initial speeds of all the agents in conflict, right before the conflict started, will be the newly adopted speed of these agents unless it exceeds their capacity of motion speed at time step k, which is $v_\ell^{\text{nc}}(k)$. In general, for $v_i^{\text{nc}}(k)$ we have:

$$v_i^{\text{nc}}(k) = \max\left\{v_i^{\max}(k), v_i(k-h) + h\Delta v_i\right\} \tag{6}$$

In (6), Δv_i and $k - h$ are, respectively, a fixed rate for the increase of speed by agent i and the most recent time step with respect to time step k when agent i has experienced a conflict. Moreover, $v_i^{\max}(k)$ is the maximum speed of agent i at time step k that depends on multiple factors: First, children, female adults, male adults, and elderly may have different maximum speeds. Second, based on the intention of the agent at time step k this maximum speed may vary, i.e., when there is no urgent danger (e.g., spreading fire in the vicinity) this maximum speed is less than when due to an urgent threat, the agent runs towards the exit, thus following a larger maximum speed. Finally, the value of $v_i^{\max}(k)$ is reduced when the agent suffers from injuries that influence its motion capabilities. The values of the maximum speeds are either identified or represented as a look-up table for the simulation model.

Remark 1: According to (4) and (5), in case agent i has no conflict with any other agents at time step k, then $\mathcal{C}_i(k) = \emptyset$ and (4) boils down to $v_i(k) = v_i^{\text{nc}}(k)$.

Remark 2: According to (6), if at time step k agent i has long enough been out of a conflict zone, then $v_i^{\text{nc}}(k) = v_i^{\max}(k)$. Else, if the agent has recently been in a conflict with the speed $v_i(k) < v_i^{\text{nc}}(k)$ and the space in front of it is now free again, the agent will increase its speed with a fixed rate until it reaches $v_i^{\max}(k)$.

The utility of an agent that has been involved in a strategic game reflects the satisfaction level of the agent regarding the achieved outcome. In the case of an emergency evacuation, the agents wish to move every time step closer to their nearest exit, in order to reduce the time that remains to their evacuation. Therefore, the utility of an agent that has just dealt with a conflict is proportional to the distance that has actually been travelled by the agent despite the conflict, versus the distance that the agent could travel within the same time interval, in case it was able to move freely with its desired speed.

Accordingly, considering T as the sampling time of the model, the utility increment for agent i at time step k is defined by:

$$\Delta u_i(k) = (-1)^{\alpha_i(k)} \gamma_i(k) \frac{v_i(k)}{v_i^{\max}(k)} T + \lceil \gamma_i(k) - 1 \rceil T^{\text{lost}} \quad (7)$$

In (7), the fraction of the actual speed $v_i(k)$ of the agent at time step k and its maximum speed $v_i^{\max}(k)$ (which would naturally be desirable for fast evacuation) quantifies the portion of the utility increment that reflects the personal benefit of the agent. Thus, for an egoist or a selfish agent who fights for its personal advantage, this term is expected to contribute more to its overall utility, compared to an altruist or a selfless agent. Both the personality (e.g., degrees of selfishness) and the ratio of various personalities in a crowd affect the overall dynamics of interactions and thus, the evacuation. For instance, personalities determine how individuals prioritise their own evacuation versus others. Moreover, a higher proportion of selfish individuals potentially cause more bottlenecks and delays, increasing the number and severity of conflicts.

Accordingly, parameters $\alpha_i(k) \in \{0, 1\}$ and $\gamma_i(k) \in [0, 1]$ are identified depending on the personality of the agent and of those that are in conflict with the agent at time step k. More specifically, if the agent exhibits a defector behaviour and acts in its own interest (i.e., exhibits egoism or selfishness) at time step k, then $\alpha_i(k) = 0$, implying that the utility of the agent due to self advantage will be increased. Else, if the agent exhibits a cooperative behaviour (i.e., exhibits altruism or selflessness) at time step k, then $\alpha_i(k) = 1$, meaning that the utility of the agent will decrease.

The value of $\gamma_i(k)$ tunes further the increase/decrease in the utility, due to the impact of physical confrontations and depending on the interaction of the agent with other agents in the conflict: For instance, if agent i exhibits an egoist or selfless character, but there are no more agents in the conflict with a defector behaviour, then agent i can win the conflict without physical confrontations and $\gamma_i(k) = 1$. However, in case $\exists \ell \in \mathcal{C}_i(k)$, such that agent ℓ also exhibits a defector behaviour, there will be physical confrontations between agent i and agent ℓ for winning the game and thus, $0 \leq \gamma_i(k) < 1$ (e.g., $\gamma = 0.5$ as is used in [41]). In fact, since dealing with a larger number of egoist and selfish agents is more likely to involve an agent in physical confrontations, the value of $\gamma_i(k)$ for an egoist or selfish agent may be proportional to the inverse of the number of all the agents with defector behaviour in this conflict.

In real-life, physical confrontations of egoist and selfish agents may cause them to fall or to be injured/harmed, which results in further delay for the agents that should deal with such consequences. Thus, in addition to adjusting the utility increment due to physical confrontations of selfish and egoist agents through tuning $\gamma_i(k)$, a fixed lost time T^{lost} is subtracted from the utility of these agents to incorporate the average time that is required for the agents to heal from the consequences (e.g., falling or being harmed/injured) of those physical confrontations. Note that in (7) the coefficient $\lceil \gamma_i(k) - 1 \rceil$ for the lost time adjusts the value of this term based on the personality of the agent and those agents that are in a conflict with it. The notation $\lceil \cdot \rceil$ represents the ceiling function, i.e., a function that maps any real value to the smallest integer value that is equal to or larger than that real value. In general, for a single agent with defector behaviour winning is evident, and since $\gamma_i(k) = 1$ and thus $\lceil \gamma_i(k) - 1 \rceil = 0$, there is no loss for the agent's utility due to the consequences of any physical confrontations.

The evacuation time estimated by (2) contributes to the cost of agent i for evacuating the building. The utility that agent i gains after handling a conflict at time step k should be subtracted from the cost. therefore, we have:

$$c_i(k) = T_i^{\text{evac}}(k) - \Delta u_i(k) \quad (8)$$

where $c_i(k)$ is the cost for agent i after resolving the conflict at time step k. From all agents $\ell \in \mathcal{C}_i(k) \cup \{i\}$, the one with the least cost wins the conflict. The winner moves to its desired position and the rest of the agents are obliged to remain in their place for another sampling time. When the game has no winner (e.g., a case where all agents in conflict exhibit a cooperative behaviour), then these agents will move according to their BDI rules.

C. HUMAN-ROBOT INTERACTIONS FOR EVACUATION

Evacuation robots should steer the trapped people towards their nearest exit. According to [66] evacuation robots should not cause any harm to people or hinder the evacuation process. Since the physical design and controlling the behaviour of the evacuation robots is out of the scope of this paper, we assume that evacuation robots are designed and programmed not to get into any conflicts with humans. In other words, if the human decides to walk away from an evacuation robot, the robot will not hinder their passage. This assumption allows to isolate and analyse the core effects of trust dynamics and strategic decision-making in evacuation scenarios, without adding uncertainties related to complex human-robot physical or strategic conflicts (which need more complex interaction models and empirical validation).

The outcome of an evacuation process and whether or not the evacuees will engage in human-robot interactions depend on the level of the trust of the evacuees in robots [58], [63]. In GT-BDI, whenever an evacuation robot and an agent are within a specific vicinity of one another, the robot initiates an interaction with the agent by showing it a direction to evacuate the building. The interaction may be terminated or followed up by the agent, depending on the initial trust level of the agent in evacuation robots and the performance of the evacuation robot that the agent has encountered. After an interaction has been launched, it continues as long as the trust level is above a scepticism threshold and the robot is in the given vicinity threshold of the agent. For instance, after agent i who is unfamiliar with the environment at time step k, i.e., $\beta_i(k) = 0$, visits an evacuation robot that performs perfectly and is able to share correct information about the environment with the agent, the familiarity of the agent with its environment enhances for the next time steps, i.e., $\beta_i(\kappa) = 1$ for $\kappa = k+1, k+2, \ldots$. This will positively impact the human-robot interactions and will allow the interactions to sustain longer. The dynamics of the trust in the course of human-robot interactions is a crucial factor in robot-assisted evacuation processes, and is thus modelled in GT-BDI, as it is explained next.

The impact of any interactive behaviour by evacuation robots on the trust of a human is not instantaneous, but the increase or decrease in the trust occurs over time. As it was explained in Section III-C, research has shown that the dynamics of the trust can be represented via a first-order differential (or difference, in the discrete-time domain) equation.

Considering the discussions provided in the related state-of-the-art literature and encapsulated in Section III-C of this paper, we propose the following saturated difference equation to model the evolution of the trust of agents in evacuation robots per time step in GT-BDI:

$$\tau_i(k+1) = \max\left\{0, \min\left\{\tau_i(k) + \delta_i\sigma(k), \tau_i^{\max}\right\}\right\} \tag{9}$$

with $\tau_i(k)$ the level of trust of agent i in evacuation robots at discrete time step k.

In modelling the trust for every human, according to [56], [57], it is common to consider a maximum trust value (indicated by $\tau_i^{\max}$ in (9)). In general, this maximum trust value varies among different people depending on their propensity to trusting evacuation robots. These individual-based variations have been incorporated into GT-BDI by introducing $\tau_i^{\max}$ as a variable of i, i.e., a variable that depends on the human whose trust dynamics is modelled.

In (9), $\sigma(k)$ models the influence of the human-robot interactions on the updated trust value of the human in evacuation robots. The discrete-time model runs according to a fixed sampling time. If during this time, no interaction is conducted, $\sigma(k) = 0$ and thus, the trust is not impacted. If the human-robot interaction has evolved in the last sampling time and has been positive, i.e., the robot has performed with no fault and has steered the human closer to their target exit, then $\sigma(k) \in [0, 1)$ is considered to model the recovery or improvement of the trust of the human in evacuation robots. The concept of reputation, which depends on the history of the interactions, may in general be used as an input to the trust update model. For details about reputation modelling see [67].

For an interaction with a faulty robot that misleads the human, $\sigma(k)$ is a negative integer with its magnitude depending on the class of the failure of the robot. The failure of evacuation robots is categorised in class 1, 2, or 3, for, respectively, the least severe (e.g., malfunction of the audio or lights of the robot), moderate (e.g., the robot is out of function), and the most significant (e.g., the robot misleads the evacuees by providing wrong information) malfunctions. In (9), δ_i is a fixed rate for the decrease of the trust of agent i, when interacting with a robot that shows a class 1 (i.e., the least severe) failure. This rate is also defined as an individualised value that may be different for various agents.

V. CASE STUDIES

We designed and implemented case studies to validate GT-BDI with respect to a benchmark model called EXODUS [68], [69], [70], [71], [72], as well as IMPACT [17], which is an agent-based model that represents the evacuation behaviour, incorporating psychological and socio-cultural aspects via a BDI framework. GT-BDI is similar to IMPACT in incorporation of psychological and social aspects in the evacuation behaviour. Additionally, GT-BDI leverages game theory to model how conflicts are handled by different evacuees, incorporating the influence of the relational and personal factors into the conflict handling behaviour of evacuees.

After validating GT-BDI, evacuation robots were included in various simulated scenarios and the impact of these robots on the evacuation process was analysed. The simulated scenarios differ in the number of evacuation robots and the percentage of robots per class of failure. The results for the evacuation time and dynamic evolution of trust in human-robot interactions are presented and discussed.

A. SET-UP FOR MODEL VALIDATION

GT-BDI was implemented via NetLogo 6.3.0 [73], an agent-based environment that has extensively been used across diverse fields due to its accessibility, ease of use, and ability to simulate complex systems with many interacting agents (see [74] for healthcare application; [75], [76] for traffic simulation; [77], [78] for applications to social systems). All codes developed for data analysis were conducted using Python. The simulations were run on 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.

1) ENVIRONMENT & PARAMETER VALUES

The simulated evacuation environment consisted of a square-shaped room of size 20×20 m^2 with a 4 m wide door per wall (i.e., overall 4 doors) with the bottom one showing the main entrance and the rest showing the emergency exits of the room (see Figure 3). This choice is due to the following reasons: First, the primary focus of this paper is on incorporating both individual cognition and interactive strategic decision making in evacuation modelling, and on including the impact of evacuation robots on the dynamics of the decision making and behaviour of humans in emergency evacuations. Accordingly, by simulating a simpler environment, we have isolated the dynamics of the human decision making that is impacted by individual and social interactions, as well as by the human-robot interactions,

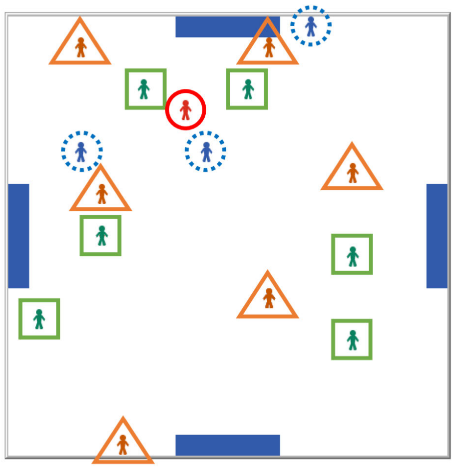

FIGURE 3. Illustration of the simulated room for the case studies: The blue rectangles along the walls represent the doors (the one across the bottom wall is the main entrance and the other 3 doors are the emergency exits). The colour and the surrounding shapes per agent show the personality of each agent. The blue dashed circles, the green squares, the orange triangles, and the red solid circles are used for, respectively, the altruists, the selfless, the egoists, and the selfish.

TABLE 2. Parameters used to model the dynamics of motion of the agents in all experiments of the case study.

Motion dynamic parameter	Value in m/s
Maximum walking speed for children	[0.50, 1.00]
Maximum walking speed for female adults	[0.90, 1.42]
Maximum walking speed for male adults	[1.00, 1.52]
Maximum walking speed for elderly adults	[0.90, 1.20]
For all categories above, when the agent perceives urgent threats, it runs with its maximum running speed that is 3 times larger than their maximum walking speed [80]	
Threshold parameter	Value in m
Distance threshold for launching a conflict with another evacuee	0.8
Distance threshold for launching an interaction with an evacuation robot	5.0
Temporal parameter	Value in ticks
Simulation sampling time	1.0
Spatial parameter	Value in m^2
Size of the room	20×20
Space occupied by each person	0.80×0.80

from any impacts of complex environmental features. Including more intricate environmental setups may overshadow the dynamic behavioural model of humans. Moreover, the environment considered is identical to that of [17], allowing for a meaningful and fair comparison.

At the beginning of each simulation, 600 agents were randomly placed across the room. The space occupied initially by each agent represented an area of about 0.8×0.8 m^2. The agents had an observation range of 5 m. At the outset of each simulation, a fire broke out from a random place, covering a circle of radius 3 m. After the fire erupted, the evacuation process started with the first agent starting to evacuate. The evacuation process ended, as soon as all the alive agents evacuated the room.

Table 2 summarizes the values for all parameters used in the case studies. The values for the maximum speed are derived from [79]. They depend only on the demographics and are randomly selected for agents of each category from the given range in the table, in order to account for various fitness and mobility capacities. As is mentioned in Table 2, in case of urgent emergencies the maximum speed of the agents increases by a factor 3, which is also based on [79].

TABLE 3. Parameters used in 2 different settings for validating GT-BDI.

Parameter	Setting 1	Setting 2
Percentage of agents with perfect environment familiarity	0%	50%
Lost time due to conflicts (T^{lost})	30 [s]	see Table 4
Percentage of children	15%	15%
Percentage of elderly	15%	15%
Percentage of female adults	50%	50%
Percentage of male adults	20%	20%
Fire breakout location	Random	Random
Initial evacuee location	Random	Random
Percentage of groups of 1 agent	100%	50%
Percentage of groups of 2 agents	0%	25%
Percentage of groups of 3 agents	0%	15%
Percentage of groups of 4 agents	0%	10%

TABLE 4. Parameter setting for incorporating game theory into GT-BDI.

	Minimum	Maximum
Percentage of **selfish** agents	10%	20%
Percentage of **egoist** agents	35%	45%
Percentage of **selfless** agents	25%	45%
Percentage of **altruist** agents	10%	20%
Lost time T^{lost}	5 [s]	5, 15, 30 [s]

In order to compare GT-BDI with EXODUS and IMPACT, first 'setting 1' inspired by [17] and given in Table 3 for the model parameters was considered. Moreover, 'Setting 2' given in Tables 3 and 4 was implemented to address further aspects that enable to analyse the impact of integrating game theory with the BDI framework. The distribution of the personalities of the simulated agents affects the choice of their game-theoretic strategies, and thus the overall evacuation time. The lost time (i.e., the time an agent loses from, e.g., falling or being pushed away, until it recovers and continues the evacuation process) based on Table 4 was modelled as a random bounded value.

The simulation time step was one tick, a measure of time in NetLogo standardized across all models and computers, i.e., it remains the same no matter how fast models and/or computers run. In our implementation of the GT-BDI model, one tick corresponds to one second for the simulated environment. During the simulations, a conflict occurred among the agents that appeared in a distance less than 80 cm from one another [41], [80]. The winner of the conflict was determined by the next time step. In other words, per interaction (corresponding to one tick) among conflicting agents, the simulator determined the winner according to (7), complying with the fact that no intellectual processes usually occur during conflicts in emergency situations [81]. This, however, does not necessarily mean that one tick suffices for complete resolution of a conflict, since the lost time T^{lost}

(see Table 4) for all agents involved will contribute to the total time needed for practical resolution of a conflict.

2) MOTION DYNAMICS

The dynamics of the motion of agents follows a simplified version of the general model given by (4)-(6). When free, agents either move according to their walking speed, which is derived from Table 2, or run with a speed that is 3 times larger than their walking speed in case they perceive a close-by danger; this determines $v_i^{\max}(k)$ for agent i in (6).

Agents reduce their speed when becoming involved in a conflict, where their adopted speed depends on the number of agents involved in the conflict. For simplification, in our implementation of the general equations given by (4)-(5), we followed the information in [82], which states that for a maximum number of 8 people per square meter the walking speed reduces to 5% of their maximum speeds, whereas for 4 people or less there is no reduction in the individual walking speeds. Thus, whenever a conflict involved more than 4 agents, we allowed the agents to adopt a walking speed that was 5% of their maximum speed as is given in Table 2.

Finally, for the term that models the recovery of the walking speed in (6), we simplified our implementation by allowing the agents (starting by the winner of the conflict) to continue moving towards their desired exit immediately with their maximum speed. For a more detailed simulation, one may associate different acceleration/deceleration rates to different categories of agents.

3) ASSUMPTIONS

The simulations for model validation are based on the following assumptions:

- **A1.1.** The fire does not propagate, allowing to focus on the impact of human decision-making without introducing additional complexity related to fire propagation effects. There is no influence from smoke on health and performance of agents either.
- **A1.2.** Each agent is either perfectly familiar with the location of all the emergency exits and the main entrance, or is only aware of the location of the main entrance.
- **A1.3.** Agents that get caught in the fire die.
- **A1.4.** The agents' personalities (altruist, selfless, egoist, selfish) remain constant during each simulation.
- **A1.5.** The lost time due to a conflict is randomly assigned to that conflict (i.e., the lost time T^{lost} is defined as a conflict-related, not an agent-related, parameter).

B. SET-UP FOR ANALYSING THE IMPACT OF EVACUATION ROBOTS IN EVACUATION PROCESSES

To evaluate the impact of adding evacuation robots on the evacuation time, we used the validated GT-BDI model. The benchmark models used in the previous section do not provide the distribution of the personalities of the agents. Thus, for making a meaningful comparison about the evacuation times for the scenarios with and without evacuation robots, we considered a personality distribution that in the validation provided close results to the benchmark models.

TABLE 5. Parameters related to the evacuation robots and for estimation of the trust dynamics via (9).

	Minimum	Maximum	Mid
Number of robots	10	100	55
propensity to trust $\tau_i^{\max}$	0.75	1.5	-
Trust recovery rate, $\bar{\sigma}_i$	0.1	0.2	-
Trust decrease rate, δ_i	0.15	0.3	-
Percentage of failing robots	0	70	35

1) PARAMETER VALUES

Simulations were conducted with the setting given in Table 5 for the robots and trust dynamics. At the outset of each simulation, the trust level of an agent was its propensity to trust. The scepticism threshold is 1, thus if (propensity to) trust was larger than 1, the agent over-trusted the robots and otherwise, the agent was sceptical about the robots. It took agents 1 s to comprehend the robot message [83], [84]. During the evacuation, each agent interacted with those robots that were in its observation range (i.e., 5 m [85]). The robots were assisting the agents to find the emergency exits that were the closest to the agents. The 3 classes of failure explained in Section IV-C were considered for the robots in all the simulations, considering the distributions given in Table 5 (deduced based on empirical findings from human-machine interactions using [58] and [63]). The value of $\sigma(k)$ in (9) for an agent at time step k was $-1, -2, -3$ when interacting with a robot with a failure of class 1, 2, 3, respectively. Each simulated robot was randomly assigned a failure class. After interacting with a failure-free robot, the trust of the agent was recovered according to its trust recovery rate $\bar{\sigma}_i$ (see Table 5).

2) ASSUMPTIONS

The simulations in this section are based on the following assumptions:

- **A2.1.** Immediate result of interacting with a robot reveals its failure class for agents.
- **A2.2.** Faulty robots can still move across the room.
- **A2.3.** After an interaction with a faulty robot, the trust of the agent in all robots in the environment decreases.
- **A2.4.** The success of human-robot interactions depends solely on the performance of the robot.

C. RESULTS AND DISCUSSIONS

First, we present the results for validating the combined GT-BDI model. In order to account for randomness in the parameter values, including the location of the fire, the initial location of the agents, and the distribution of the personalities among the agents, the model was simulated several times for both settings 1 and 2 (see Table 3). More specifically,

TABLE 6. Total evacuation time for GT-BDI with 3 settings, compared to IMPACT and benchmark EXODUS: Setting 1 is when game-theoretic interactions are very simplistic since identical social interactions are considered for all agents; setting 2 is when game-theoretic interactions are detailed by assuming various personality distributions and interactive behaviours for agents; and real-life setting is when game-theoretic interactions are included and a close-to-real personality distribution for the agents is considered.

	EXODUS	Impact	GT-BDI setting 1	GT-BDI setting 2	GT-BDI real-life setting
Total evacuation time	585.00 s	516.6 s	466.90 s	499.17 s	541.43 s
Relative error	–	11.69%	20.19%	14.67%	7.40%

each simulation with a specific personality distribution for the agents ran 60 times. The precision of GT-BDI in estimating the overall evacuation time was compared to IMPACT and to benchmark EXODUS. Next, evacuation robots were included in the simulations, in order to assess the potential improvement of the evacuation process, in terms of the total evacuation time.

1) RESULTS AND DISCUSSIONS FOR MODEL VALIDATION

a: MODEL PRECISION

Table 6 shows the total evacuation time of GT-BDI, IMPACT, and benchmark EXODUS: In setting 1 (see Table 3), no distinction among the agents' personalities is considered. In setting 2 (see Table 4), different personalities are assigned to the agents with distributions that follow the values in the table. We assumed that the majority of the population falls within the moderate personality spectra, i.e., egoist and selfless, whereas the selfish (having no interest for saving others) and altruists (having no interest in saving themselves when other agents can be saved) form a smaller proportion of the population. There is no knowledge about these personality traits for the benchmark model. Thus, we also determined the average of the evacuation times for 150 runs for a range of personality distribution (15% to 30% altruists, 35% to 40% selfish, 25% to 40% egoists, the remaining being selfless), which was proven via extensive simulations to generate the closest values to EXODUS. This is called the real-life setting in Table 6.

Table 6 shows that the average evacuation time of GT-BDI for setting 1, setting 2, and real-life setting are, respectively, 466.92 s, 499.17 s, and 541.43 s, which correspond to errors of, respectively, 20.19%, 14.67%, and 7.40%, with respect to the evacuation time 585.00 s estimated via EXODUS. The largest error is corresponding to setting 1, where no variation in the game-theoretic interactive behaviours of the agents is considered. Figure 4 illustrates that in this case the least and largest values estimated for the evacuation time are, respectively, 423.18 s and 504.31 s, with the lower and upper quartiles being 449.36 s and 490.18 s, respectively. When GT-BDI is simulated with setting 2, the error is reduced for around 6%, and from Figure 5, the least and largest evacuation times are, respectively, 455.25 s and 560.57 s (which is an outlier), and the lower and upper quartiles are 486.18 s and 512.67 s, respectively. Thus, in general, including different interactive strategies via incorporation of game theory into BDI improves the precision of the model. From the real-life setting, it is deduced that the personality distribution

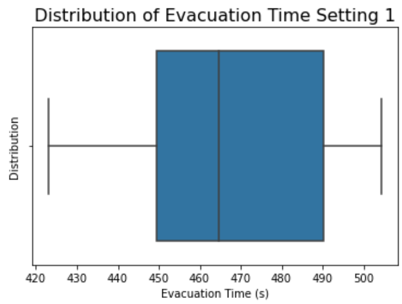

FIGURE 4. Distribution of the estimated evacuation time using GT-BDI with setting 1.

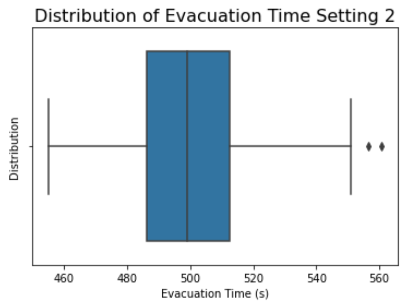

FIGURE 5. Distribution of the estimated evacuation time using GT-BDI with setting 2.

TABLE 7. Average evacuation success per personality from GT-BDI.

Personality type	Successfully evacuated
Selfish	96.61%
Egoists	95.91%
selfless	96.01%
Altruists	96.69%
Average	96.32%

that results in the most precise evacuation time differs from that in Table 4. The main difference is regarding the manifestation of extreme behaviours, especially selfishness, which in a catastrophic evacuation process turns out to be significantly larger than what is expected in a normal population distribution, as shown in Table 4.

b: EVACUATION SUCCESS PER PERSONALITY

Table 7 and Figure 6 show the percentage of agents per personality for setting 2 that successfully evacuated the room for the simulated scenarios. For the altruists, the evacuation success rate is bounded by the lower and upper quartiles of, respectively, 96.47% and 96.89%, and has an average value

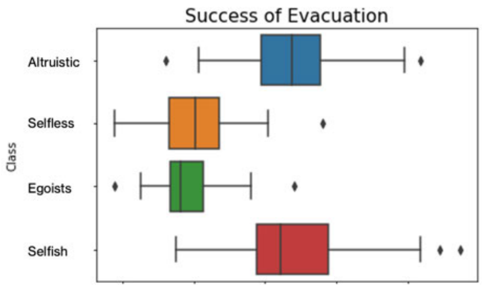

FIGURE 6. Percentage, per personality, of agents that successfully evacuated the room.

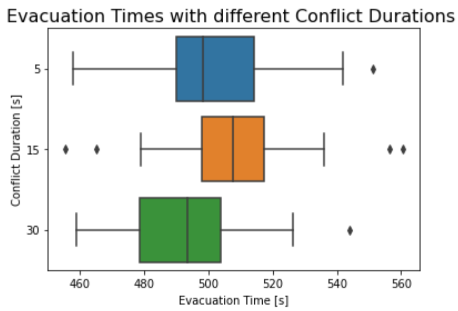

FIGURE 7. Distribution of the estimated evacuation time using Gt-BDI with setting 2for three different maximum conflict lost times (5 s, 15 s, 30 s).

of 96.69%. The lower and upper quartiles for the evacuation success rate of selfless agents are, respectively, 95.83% and 96.17%, with an average value of 96.01%. For the egoists, the evacuation success rate varies between quartiles 95.83% and 96.06%, where the average is 95.91%. Finally, for the selfish agents, the evacuation success rate varies between the lower and upper quartiles of, respectively, 96.44% and 96.96%, where the average is 96.61%. From Figure 6, the evacuation success rates of the selfish and egoist agents show, respectively, the largest and the smallest inter-quartile ranges.

While the difference in successful evacuations for various personalities was very small, the altruists, followed by the selfish, were slightly more successful than the selfless and the egoists. On the one hand, the altruists do not rush to the exit right away, but spread across the room. On the other hand, the selfish are more likely to end up congested at the exists. Thus more conflicts are expected for the selfish that may contribute to a failure in their evacuation. The selfless and egoists are milder versions of the altruists and the selfish, respectively. Thus, it is expected that the selfless are in general more successful than the egoists in evacuation, which is confirmed by the results in Table 7. Finally, since there are more selfless and egoist agents in the simulations than the altruist and selfish agents (see Table 4), this may contribute to the larger number of selfless and egoist agents to be deceased.

c: CONFLICTS AND LOST TIMES

The results corresponding to GT-BDI with setting 2 show that different conflict lost times impact the average evacuation time (see Figure 7). Interestingly, the average evacuation time is the smallest (i.e., 492.12 s), when the conflicts can last the longest (i.e., 30 s). When the conflicts take up to 5 s, the average evacuation time is 503.05 s. Finally, for a maximum lost time of 15 s, the average evacuation time is 507.25 s. In the scenarios, where GT-BDI performs closely to EXODUS, the average conflict lost time is 15.63 s. In fact, in 31.25% of conflicts, the lost time was 5 s, in 43.75% it was 15 s, and in 25% it was 30 s.

Additionally, it is observed from the simulations that the number of conflicts during evacuation processes varies with conflict lost times: For lost times lasting up to 30 s, simulations showed an average number of 6781.76 conflicts, with an average evacuation time of 492.12 s. For conflicts that lasted up to 15 s, on average 6862.37 conflicts were observed and the average evacuation time was 507.25 s. Finally, lost times up to 5 s led to 6807.49 conflicts and an evacuation time of 503.05 s, on average.

In summary, although it may be counter-intuitive, smaller conflict lost times can lead to larger evacuation times. This is because quicker conflict resolutions increase the likelihood of subsequent conflicts, since agents are more likely to encounter others. This effect depends on personalities and initial locations of the agents, influencing the frequency and locations of conflict occurrence. This implies that more conflicts may arise, when the lost time is on average smaller, such that the accumulation of all these lost times results in a larger time being wasted during the evacuation process. This is confirmed for the conducted simulations by the number of conflicts that arise for different conflict lost times. On the one hand, when two conflicting agents resolve their conflict faster and continue the evacuation, they will be more prone to getting involved in other conflicts. On the other hand, when the conflict between two agents lasts longer, the agents around them evacuate the room, and hence the chances are smaller for these two agents to get involved in future conflicts. These phenomena, however, in general also depend on the initial location and the personality distribution of the agents.

2) RESULTS AND DISCUSSIONS FOR EVACUATION ROBOTS

In order to evaluate the impact of deploying evacuation robots on the evacuation process, various simulations including different number of robots with varying degrees of failures were conducted. In these simulations, the agents were distributed according to 16.56% selfish, 34.06% egoist, 35.31% selfless, and 14.06% altruists, since this particular distribution showed close-to-benchmark results (with an average evacuation time of 533.12 s) in multiple simulations. The number of the evacuation robots varied between 10 (each robot supporting about 60 agents) and 100 (each robot supporting about 6 agents). A certain number of random robots failed, randomly associated with one of the 3 failure classes. Two cases of simulations were considered: In the first case, the robots were assumed to be stationary, whereas in the second case, the robots moved randomly in the room, avoiding the fire. By moving within the room, the robots were expected to encounter and assist more evacuees. Per case,

TABLE 8. Average evacuation time versus the number of robots for stationary and non-stationary robots.

Robot number	Stationary case	Non-stationary case	Improvement
10	353.43 s	206.15 s	41.67%
55	193.92 s	91.39 s	52.87%
100	143.37 s	74.28 s	48.19%

TABLE 9. Average trust versus the percentage of failed robots for stationary and non-stationary robots.

Failed robots	Stationary case	Non-stationary case	Improvement
0%	0.37	0.5	35.14%
35%	0.29	0.36	24.14%
70%	0.27	0.29	7.41%

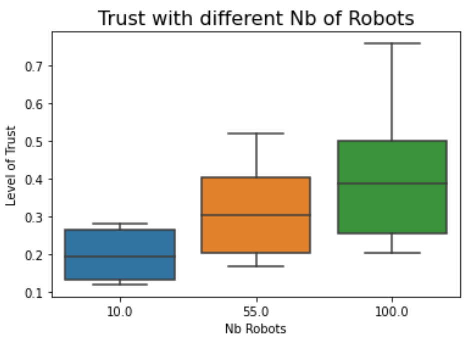

FIGURE 8. Distribution of trust versus the number of robots for the stationary case.

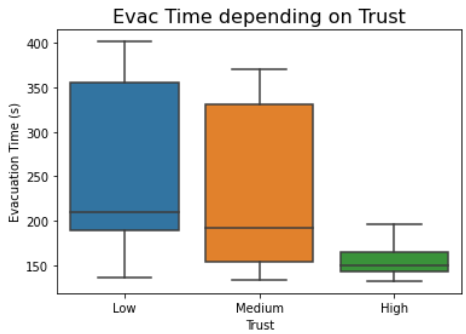

FIGURE 9. Distribution of the average evacuation time versus different trust levels for the stationary case.

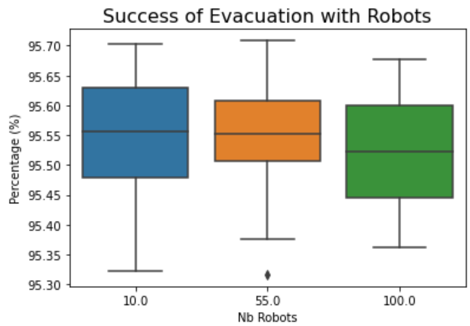

FIGURE 10. Distribution of the evacuation success rate versus the number of robots for the stationary case.

4320 simulations (each repeated 60 times) were performed to account for the randomness that is given in Table 3.

a: STATIONARY ROBOTS

Figure 8 shows that increasing the number of the stationary evacuation robots leads to a higher average (across all agents and the entire simulation window) trust, with an average trust of 0.20, 0.32, and 0.41 for, respectively, 10, 55, and 100 robots.

The presence of evacuation robots also significantly reduced the average evacuation time from 533.12 s for similar simulations, but without robots: In particular, Table 8 shows that the average evacuation time versus the number of robots for 10, 55, and 100 robots is, respectively, 353.43 s, 193.92 s, and 143.37 s, showing a reduction of, respectively 33.71%, 63.63%, and 73.11% with respect to the no-robot case.

From Table 9, for the stationary robot case, when all the interactions are successful, the average trust is 0.37, whereas for 35% and 70% failed interactions, the average trust is, respectively, 0.29 and 0.27. Thus, the difference (27.56%) between the average trust for purely successful and few failed interactions is more significant, compared to the difference (7.41%) for few and many failed interactions.

Based on Figure 9, the indirect influence of the robots failures through trust on the average evacuation time is evident: Trust was categorised into low, medium, and high, with an average of 0.1842, 0.3507, and 0.5918, respectively. The plot shows that a low trust leads to a larger average evacuation time of 260.76 s, whereas a medium and a large trust, result in average evacuation times of, respectively, 220.42 s and 156.31 s, showing an improvement of, respectively, 15.47% and 40.06% compared to the low-trust case.

With stationary robots, on average, 95.54% of the agents were evacuated successfully. The lower and upper quartiles and the minimum and maximum for the evacuation success rate were 95.47%, 95.61%, 95.32%, and 95.71%, respectively. As is shown in Figure 10, these values are not significantly different.

b: NON-STATIONARY ROBOTS

Similarly to the stationary case, the number of moving robots varied according to 10, 55, and 100. The robots were placed and moved randomly within the room, avoiding the fire. A given number of robots failed to steer the agents to the closest exit, thus negatively affecting the trust of the agents in the evacuation robots. Figure 11 illustrates that, similarly to the stationary case, when the number of the moving evacuation robots increased, so did the average (across the agents and the simulation window) trust, with its values being 0.27, 0.43, and 0.47 for, respectively, 10, 55, and 100 evacuation robots. These trust values are larger for the non-stationary evacuation robots, compared to the stationary robots according to the following percentages (given respectively for 10, 55, and 100 robots): 35.00%, 34.38%, and 14.63%.

The average evacuation time versus the number of evacuation robots for the non-stationary case is given in Table 8. While with 10 moving robots the average evacuation time was 206.15 s (showing an improvement of 41.67% compared to the stationary case, as given in Table 8), with 55 and 100 moving robots the average evacuation time was, respectively, 91.39 s and 74.28 s, showing an improvement of, respectively, 52.87% and 48.19% compared to the stationary case.

Table 9 shows that when none of the evacuation robots failed, an average trust of 0.50 was obtained during the simulations, whereas when 35% and 70% of the robots failed, the average trust was, respectively, 0.36 and 0.29, which showed an improvement of respectively 35.14%, 24.14%, and 7.41%, compared to the stationary case. Thus robots, in general, seem to be more successful in gaining the trust of the agents when put in a non-stationary setup, despite showing similar failures as stationary robots.

TABLE 10. Average evacuation time versus the percentage of failed robots for stationary and non-stationary robots.

Failed robots	Stationary case	Non-stationary case	Improvement
0%	369.82 s	122.61 s	66.85%
35%	370.27 s	123.56 s	66.63%
70%	401.57 s	125.64 s	68.71%

From Table 10, the average evacuation time was also less affected by the failure of the non-stationary robots, compared to when robots were stationary. In fact, for the no failure case and for the 35% and 70% failure cases, the average evacuation time showed a reduction of above 66% compared to when stationary robots were used.

The impact of the trust of the agents in robots on the average evacuation time for non-stationary robots is illustrated in Figure 12. For a low, medium, and large trust level, the average evacuation time was 156.12 s, 124.35 s, and 84.98 s,, respectively, that are 40.13%, 43.58%, and 45.63% less than when stationary robots are used with the same levels of trust (see Table 11). With moving robots, on average, 96.30% of the evacuees were evacuated successfully, which is a bit larger than with stationary robots. However, we simulated a stable health condition for all the agents while evacuating. If the negative impacts of heat, smoke, and injuries are also modelled, it is expected that due to the significantly larger evacuation times with stationary robots, more agents will be deceased before evacuation is complete. The lower and upper quartiles and the minimum and maximum values for the evacuation success rate are, respectively, 95.95%, 96.53%, 95.53%, and 97.28% (see Figure 13).

TABLE 11. Average evacuation time versus trust for stationary and non-stationary robots.

Trust	Stationary case	Non-stationary case	Improvement
Low	260.76 s	156.12 s	40.13%
Medium	220.42 s (−15.47%)	124.35 s (−20.35%)	43.58%
High	156.31 s (−29.09%)	84.98 s (−45.57%)	45.63%

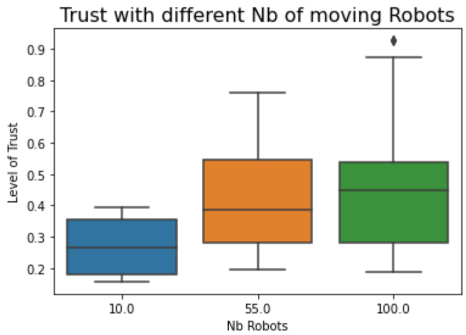

FIGURE 11. Distribution of trust versus the number of robots for the non-stationary case.

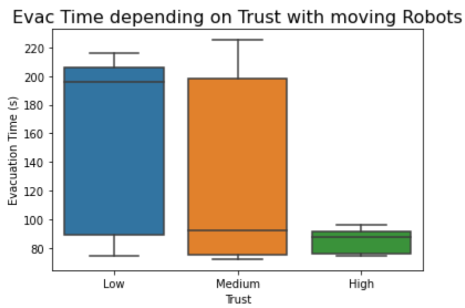

FIGURE 12. Distribution of the average evacuation time versus different trust levels for the non-stationary case.

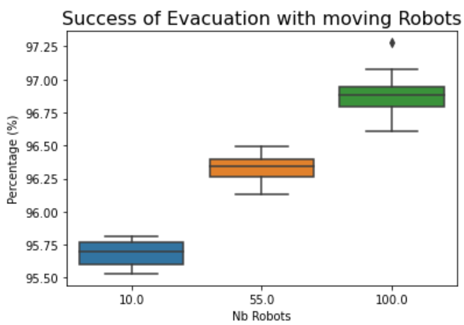

FIGURE 13. Distribution of the evacuation success rate versus the number of robots for the non-stationary case.

VI. CONCLUSION AND TOPICS FOR FUTURE WORK

During search and rescue missions, the time spent on accessing victims and assisting them to evacuate the disaster scene is crucial. In order to improve the disaster response, especially for indoor evacuations, understanding human decision making during emergency evacuation is essential.

Computational simulation models are valuable tools for understanding the individual behaviour and the interactions of evacuees. Existing evacuation models do not capture simultaneously both the individual and the group behaviour of the evacuees. Belief-desire-intention (BDI) is a cognitive framework that models individual decision making of rational agents, whereas game theory models the strategic decision making of such agents in their social interactions. This paper combined both frameworks in order to provide a comprehensive model of human decision making during indoor evacuations. Extensive simulations showed that integrating a game-theoretic point-of-view into the BDI framework improves the performance of the resulting evacuation model and makes it more realistic. The game theory module requires to receive the distribution of the agents' personalities, as well as their lost time during conflicts.

We next used the model that was already validated with experimental data based on [17] to assess the impact of including evacuation robots that assist the evacuees in indoor evacuation processes. Human-robot interactions in life-threatening conditions of search and rescue is hypothesised to have a meaningful dependency on the trust of humans in these robots. We modelled this trust via a first-order dynamic equation, and considered two sets of simulations, with stationary and non-stationary evacuation robots. The results of the simulations showed that evacuation robots reduced the overall evacuation time, where with increasing the number of the robots, the average trust was significantly improved. Moreover, the average trust of the agents in the robots was higher when robots were non-stationary. This influence was even larger when, instead of stationary robots, evacuation robots moved across the room.

The computational complexity of the GT-BDI model grows with the number of agents and their interactions during conflict resolution. As the beliefs, desires, and intentions of the agents evolve, the model requires frequent updates, which can be computationally intensive for large-scale systems. Accordingly, addressing scalability challenges for large numbers of agents requires optimisation techniques or parallel computing.

Suggested directions to expand the current research include proposing and validating combined architectures for integrating GT-BDI with state-of-the-art pedestrian dynamic models, e.g., social force models. Additionally, the analysis of robot-aided evacuation must be enhanced and made more comprehensive by including more complex environmental features that will impact the evacuation behaviour of humans. For instance, assuming static fire may reduce the realism of simulations, when real-world fires are dynamic and influence movement, decision-making, and health status of evacuees over time. Moreover, despite their advantages, current simplified rooms used in our case studies limit the possibilities to model environment dynamics and potential scale effects. Thus, future improvements involve adding stairs, narrow corridors, rubble, and dynamic models of fire and smoke propagation that should be introduced incrementally to the simulations in order to ensure that the observed changes in the behavioural dynamics are correctly attributed to the added environmental factors. Using extensive real-world data for the modelled dynamics of movement and for the human-human and human-robot interactions, in order to verify and validate GT-BDI based on realistic scenarios is an important next step. Moreover, while our model assumes cooperative interactions among humans and robots, conflicts can arise in real scenarios that should be incorporated in future research.

Further topics include performing a sensitivity analysis to further assess how variations in trust parameters influence trust dynamics and evacuation efficiency, analysing the crowd emergency behaviour to identify personality variations based on the situations that need to be incorporated into the game theory module of GT-BDI; incorporating the intention of helping other agents into both the BDI framework and the game-theoretic interactions; making distinction in the behaviour of agents per relational group, based on the nature of relationships (e.g., spouse, child, colleague, friend); and making the trust dynamics equation more rigorous by including the impact of, e.g., appearance of the robots, education/occupation of the agents, transparency of the robots decisions for the agents. Additionally, alternative modelling approaches for extension to non-linear trust models (e.g., non-linear difference equations) should be considered. Finally, systematic control methods may be considered to move the evacuation robots within the disaster environment with the aim of optimising various objectives of search and rescue, including the evacuation time and the number of saved victims.

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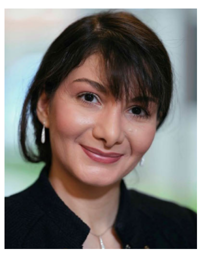

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