Integrating a Human Behavior Model within an Agent-Based Approach for Blasting Evacuation

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Abstract: *Several studies on Emergency Management are available in literature, but most of them do not consider how the human behavior during an emergency can affect the evacuation process. Therefore, the novel contribution of this paper is the implementation of an Agent-Based Model to describe the evacuation, due to a blast in a public area, integrated with a human behavior analytical model. Each agent has its own behavior that is described in a layered framework. The first layer simulates the "agent's features" function. Then, an "individual module" describes dynamically the emotional aspects using (i) the Decision Field Theory, (ii) a stationary stochastic model and (iii) the results coming from a questionnaire.*

An agent-based model with integrated human behavior is proposed to test critical infrastructures in emergency conditions without performing full scale evacuation tests. Analyses could be performed both in real time with a hazard scenario and at the design level to predict the system response to identify the optimal configuration. Therefore, the development of the proposed methodology could support both designers and policy makers in the decision-making process.

1 INTRODUCTION

Nowadays infrastructures are complex systems and they are vital parts of modern societies all over the world. As the communities grow, the infrastructures interconnection level increases, as well as their vulnerabilities towards natural and manmade events (Cimellaro et al., 2014; Cimellaro and Solari, 2014; Kammouh et al., 2018).

Agent-based models (ABM) are used to simulate complex and heterogeneous systems such as infrastructures and they can be applied in a vast range of fields like biology, business problems, ecology, social science, technology, earth science, network theory. An "agent" is an entity with a set of characteristics and rules. Agents can represent individuals, groups, companies, infrastructures, etc. They can interact each other and are flexible, having the ability to learn and to adapt their behaviors. Modeling agents' behaviors and the reciprocal interactions is possible using rules or logical operations that can be formalized by equations. It is also possible to consider individual variations in the behavioral rules ("heterogeneity") and random influences or variations ("stochasticity") (Helbing & Balietti, 2011).

ABMs can accommodate randomness and details required in emergency evacuation procedures, allowing experimental tests, which are not usually possible in a real environment (Shendarkar et al., 2008). Therefore, ABMs can guide designers and legislators in improving the infrastructure responses during an emergency.

Emergency evacuation is the movement of people from a potentially dangerous place to a safe place due to threat or occurrence of a disastrous event. The possible causes for evacuation include earthquakes, building fires, blasts, military attacks, etc. (Yuan & Tan, 2007).

In ABM several algorithms and strategies for analyzing emergency evacuation have been developed. A *general crowd model* with the flexibility to incorporate different behaviors under different scenarios is presented by Sun and Wu (2014). Nejat and Damnjanovic (2012) develop a preliminary time-space ABM in the context of post-disaster recovery for housing re-establishment, accounting a game-theoretical approach in the aftermath of disasters. Forcael et al. (2014) propose a simulation model to find out the optimal evacuation routes, during a tsunami using *ant colony algorithm*, inspired by the ability of ants to establish the shortest path from their nest to a food source. D'Orazio et al. (2014) suggest an innovative approach to earthquake evacuation through ABM based on the analysis of videotapes related to real events.

Focusing on evacuation approaches in 3-D buildings, a model of pedestrian movements is proposed and calibrated with empirical data by Chu (2009), providing information on hazard mitigation performance of a facility design. Algorithms for safest and balanced routes in buildings with multi-epicenters event is proposed by Zverovich et al. (2016), considering the relevant semantics of 3-D buildings.

Human perception in pedestrian evacuation simulation using fuzzy logic has been also developed converting the qualitative physical laws of pedestrian motion into a fuzzy system (Zhu et al. 2008, Dell'Orco et al. 2014, Fu et al. 2016).

Moreover, research groups have also created specific software for evacuation simulation for special emergency and environment conditions. E.g. the Greenwich Fire Safety Engineering Group has developed EXODUS with toolboxes (maritime, building, rail) for fire evacuation simulation and pedestrian circulation analysis to meet the challenging demands of performance based safety codes (Galea et al. 2004).

Thus, from the literature review, it appears that the evacuation scenario in ABM is usually approached in analogy with natural ecosystems, peripheral analyses or supported by theories from different fields, without considering the human behavior. First in Cimellaro et al (2017) for earthquake evacuation scenario the implementation of anxiety as ABM input parameter has been considered by using available experimental data.

In this paper, an ABM model that describes the emergency evacuation after an explosion is presented, where the personal injuries are function of the intensity of the detonation and of the distance from the bomb. The novelty of this approach with respect to existing literature comprises the insertion of the human behavior (e.g. emotions, irrational behavior and altruism) in the simulations (Figure 1), as from the inspiring work by Crowne & Marlowe (1960).

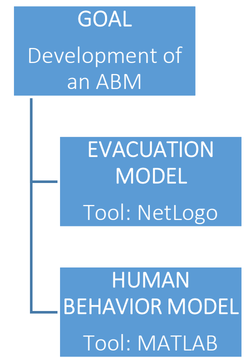


Figure 1. Research goal.

In Cimellaro et al. (2017) the influence of the human behavior has already been considered for the case of earthquake event. Differently, in this research the effect of the human behavior after an explosion has been considered. Furthermore, an alternative approach that includes a specific survey for the considered problem is used due to the lack of experimental data in literature. The influence of special agents (guardians) in rescuing other agents who are injured is also herein investigated, as well as the effect of the geometry of the environment in the emergency evacuation process.

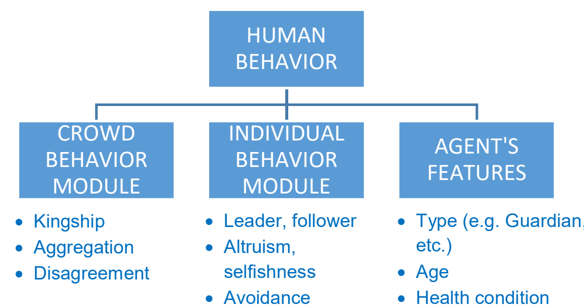


Figure 2. Main factors influencing the human behavior.

The human behavior is a complex mechanism influenced by culture, attitudes, emotions, values, ages, perception and many other aspects as shown in Figure 2 that summarizes its main components. However, during an emergency, only few components affects the evacuation process that is main driven by the individual behavior and the agent features (Challenger 2009).

Following the general approach in Figure 2, the main factors that influence the human behavior are:

1. *The* crowd *behavior*, which include kingship, aggregation, or disagreement phenomena. However, in emergency evacuations, the dominance of individual characters, e.g. as leader or follower, is primarily important over crowd movement, when only a few crowd members have information about the unfolding situation (Challenger 2009).

2. *The individual behavior,* which considers the emotional aspects (e.g. altruism) of a person in emergency evacuation. This factor might vary from person to person and through the time so it can be considered as a *dynamic* component.

3. *The features* which include the agent's type (e.g. guardians, etc.), the age and the health condition. These features remain unchanged during the simulations (*static*).

In the proposed methodology, the *evacuation time* is the main response parameter and it is used to evaluate the efficiency and the safety of the infrastructure. The evacuation time is the time needed for the last pedestrian that is able to evacuate (not severely injured) to leave the building or reach a safe location.

In order to test the proposed methodology, two different ABM evacuation models related to a museum and a metro/train platform are developed.

2 PROPOSED METHODOLOGY

2.1 The human behavior

Challenger (2009) studied the behavior of the crowd using real emergency evacuation data, showing that in those conditions the most frequent individual phenomena are the *leader-follower relationship*, together with the *altruism behavior*. Therefore, exclusively the *agent's features* and the *individual behavior* in Figure 2 are implemented in the proposed methodology for simulating the emergency evacuation. The first ones represent the *static* component, a series of default features, which remain unchanged throughout the simulation and are used to describe the agent predictable behavior. Instead, the *dynamic* component, unpredictable because driven by emotions, is modelled using the *Belief-Desire-Intention (BDI)* (Bordini et al., 2007).

The adopted BDI paradigm is the modified version proposed by Zoumpoulaki (2010) which is able to reproduce the human decision-making process with the incorporation of *personality* and *emotions*. It is implemented through the *Decision Field Theory* (DFT), developed by Townsend & Busemeyer (1995) and Busemeyer & Diederich (2002), subsequently extended (EDFT) by Lee et al. (2008) to cope with the dynamically changing environment. The Decision Making Module is the core of a BDI and it is discussed in the following sections.

2.2 Agent's models

Three agent's rules are proposed to describe the human behavior in the ABM model: (i) *the base model*, (ii) *the static leader follower-behavior* and (iii) *the dynamic leader follower-behavior.*

The *base model* is characterized by the static rules. Agents look for an emergency exit in their eye's range. If they found one, they evacuate through the emergency exit. Otherwise, the agents retrace the path already followed, rather than running an unknown path.

The *static leader follower-behavior* model introduces an additional static rule with respect to the base model. If an agent sees a leader within his eye's range, he automatically becomes a follower. This model is still quite far from reality because the agents cannot decide how to behave.

Instead, in the *dynamic leader follower-behavior* the agent decides how to behave, e.g. whether to follow or not a leader using the BDI. Right after an explosion, the psychological profile of an agent emerges, therefore during the simulation a certain percentage of agents become leaders. The other agents are classified as followers, but this does not mean that they necessary follow a leader. In fact, they can decide if following or not a leader depending on both *rational* and *irrational* factors.

The rational factors can be the health status, the location of the emergency exit, etc. Instead, the irrational ones are the emotions, so depending on its emotional state, an agent can decide to listen to them or not. For example, the altruism behavior depends on both the agent psychological profile and its emotions. So, altruism in an agent can occur if the injured agent is within his eye's range and if he is not injured.

Two phases are implemented in the proposed ABM: (i) the *normal* phase when the agents are involved in typical actions and they move slowly in the spatial environment. The *emergency* phase (ii), after the explosion, when the agents move fast towards a safe place, the emergency exit. Additional agents called "guardians" are also included in the simulations to rescue other agents who are injured.

The three agent's rules are implemented to describe the human behavior during the evacuation and belongs to the emergency phase. Furthermore, to perform a consistent comparison between different agent's rules, each simulation implements exclusively one type of agents' rule at a time.

2.3 Belief-Desire Intention paradigm

The Belief-Desire-Intention paradigm has been used to simulate the decision-making process. *(i) Beliefs* are information that an individual possesses regarding a situation. They may be incomplete or incorrect, e.g. due to human perception. *(ii) Desires* are the conditions that a human would like to happen. *(iii) Intentions* are desires that a human is committed to achieve. Figure 3 shows the interaction of the BDI modules with the ABM environment.

The core of BDI is the *Decision Making Module* in Figure 3 that is implemented through the *Extended Decision Field Theory* (EDFT). It provides a dynamic and probabilistic mathematical approach to simulate the human decision making process under uncertainties. Both the changing environment and the time variation affect it.

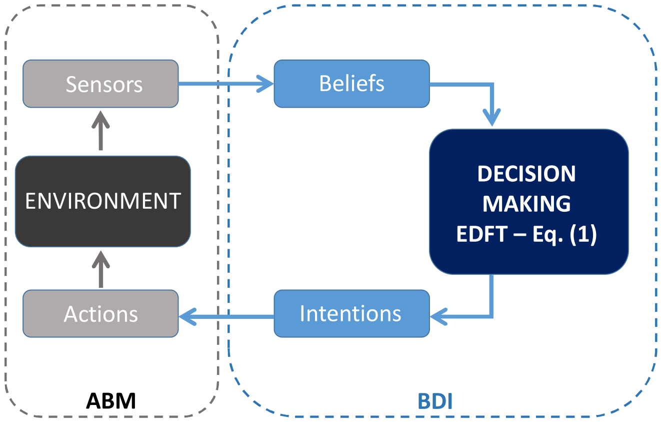


Figure 3. Interaction of the human behavior modules with the ABM environment (adapted from Lee & Son, 2008).

The EDFT can update the agent's behavior model based on the *dynamic environment*, the *subjective evaluation* and the *weight factors* associated to each alternative.

Mathematically, EDFT allows computing the dynamic evolution of preferences P among m options expressed by an agent over time using Equation (1).

$$P(t+h) = SP(t) + CM(t+h)\cdot W(t+h) \qquad (1)$$

where $P(t)^T = [P_1(t), P_2(t), \ldots, P_m(t)]$ represents the preference state in percentage (0-1 as 0-100%) and $P_i(t)$ is the strength of the preference corresponding to option i at time t. The preference state is updated at every time step h.

The first term on the right side of Equation (1) provides the memory effect. It is the product of the preference chosen at the previous state and the *Stability Matrix* S ($m\times m$), where m is the number of options and n is the number of attributes. The stability matrix S is assumed to be constant (*static*) and symmetric. It provides the effect of the preference at the previous state (the memory effect) and the effect of the interactions among the options. The diagonal terms of the S matrix are the memory for the previous state preferences and they are assumed to have all the same value. The off-diagonal terms are the inhibitory interactions among competing options and are typically relatively small. The memory effects are set to decay slowly by setting a high value to the diagonal elements.

The second term characterizes the EDFT, reproducing the way the human behavior copes with the *dynamically* changing environment. In particular it is achieved by the matrix M and W that may change during the decision deliberation. This last is the peculiar aspect that differentiates DTF from EDFT (Lee et al. 2008).

M is the *Value matrix* ($m\times n$) and represents the subjective evaluations (perceptions) of a decision-maker for each option on each attribute. If the evaluation value changes dynamically according to the environment, the matrix M is constituted with multiple states.

W is the weight vector ($n\times 1$). It allocates the weights of attention corresponding to each column (attribute) of M. In the case that M is composed of multiple states, each weight $W_j(t)$ corresponds to the joint effect of the importance of an attribute and the probability of a state. $W(t)$ changes over time according to a stationary stochastic process.

C is the *Contrast matrix* ($m\times m$) that compares the weighted evaluations of each option, $M(t+h)\cdot W(t+h)$. If each option is evaluated independently, then C will be I (identity matrix). In this case, the preference of each option may increase simultaneously (see Equation 1). Alternately, the elements of the matrix C may be defined as $c_{ii}=1$ and $c_{ij} = -\dfrac{1}{(m-1)}$ for $i\neq j$ where m is the number of options (Lee et al., 2008). Through such definition of C diagonal and off-diagonal terms, preferences increase of one option, lowers the preference of alternative options, and the sum of the elements of $CM(t+h)\cdot W(t+h)$ is zero.

The value matrix M and the W weight vector are the dynamic (evolutionary) elements of the EDFT. Therefore, they are the factors that mostly influence the human behavior of the agents.

It is worth underlining how in Cimellaro et al. (2017) for the case of earthquake event, the second term in Equation (1) is defined through a proposed anxiety formulation that depends on the shaking level. An existing work from literature (Takahashi et al 2004, 2010) with extensive tests on shaking table for modelling the human behavior in earthquake conditions is used to identify the anxiety model parameters and its implementation in the ABM. However, that approach can not be used in the present work because a different emergency condition is considered and experimental data on the human behavior in case of blasting events are lacking. Thus, the human behavior has been defined through the contrast matrix C, the value matrix M and the weight vector W, all identified with the specific survey.

2.4 Calibration of the parameters

The calibration of the agent's behavior for the ABM simulations is performed through a questionnaire that has been prepared using the guidelines given by the Theory of Planned Behavior - TPB (Ajzen, 1991; 2006; Cimellaro et al., 2018). Appendix A essentially summarizes the procedure for determining the parameters of the human behavior model and how the results of the survey are employed for calibrating the matrix M and obtaining the vectors W and P.

2.5 Implementation of the human behavior model

The human decision-making process implemented through EDFT is shown in Figure 4.

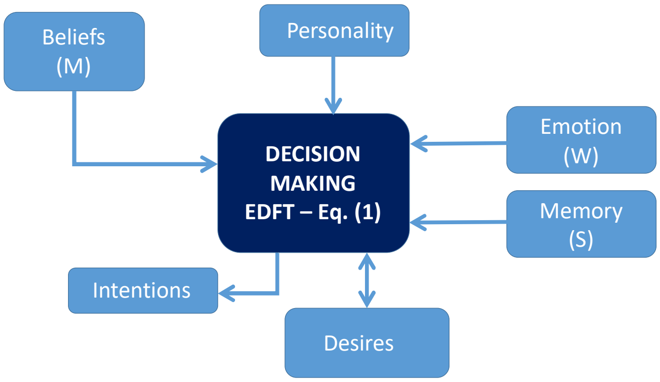


Figure 4. EDFT architecture.

The *beliefs* block filters the agents' environment perceptions in three cases:

1. when the agent is influenced by the knowledge of the environment and by its role. For example, a guardian knows the location of the emergency exits while the visitor does not.
2. When the emotional state influences the agent's perception of danger.
3. When the physical conditions (injured / not injured) affect the human behavior.

The subjective evaluations (perceptions) of an agent are described by a matrix M that may change dynamically through the time, because of the environment and the logic sense of the decision maker.

Each agent has a specific psychological profile (*personality block*) that leads him to perform actions. They are: leader/ follower and altruism/selfishness. The leader accepts a higher risk and he is more determined, therefore he can gather around him a group of people that follow him toward the emergency exit. The follower moves together with the leader or a group of people and hardly evacuates by his own. Moreover, the agents can also be altruist towards injuries, even if their final decision is affected also by their physical conditions.

The *Emotion* is the irrational component of the human psyche and it is described by a weight vector W that is associated to a stationary stochastic process. Analytically is given by:

$$W_{k,q}(t+h) = \begin{pmatrix} W_{\mathrm{k,q,n}} \\ W_{\mathrm{k,q,n}} \\ W_{\mathrm{k,q,n}} \end{pmatrix} \quad (2)$$

where W is the weight vector ($n \times 1$); n are the attributes of the human behavior (n=3 in the present study, as explained in the Appendix A); $W_{k,q,n}$ is a random variable within a fixed data range; the subscripts k and q are the indices that correspond respectively to: k=Leader/Follower, q= is one of the eight agent conditions after the explosion ranging from 1 to 8.

Even the *Memory* influences the decision-making process, through the first term of Equation (1) that is the product of the previous chosen preference P and of a stability matrix S. The diagonal elements of the S matrix are the memory of the previous step preferences, while the off diagonal elements are the inhibitory interactions among competing options.

The *Desires block* describes the desires to do an action such as the need to help an injured person or a family member or the necessity to find an emergency exit.

Finally, in the *decision making block* all the previous modules converge (Figure 4). This block is analytically described by Equation (1) that determines the *preference P* to perform an action iteratively following this structure: preferences, intentions, and actions.

More details on the human behavior model are given in Appendix A, while the computational flow is described in Appendix B.

3 CASE STUDIES

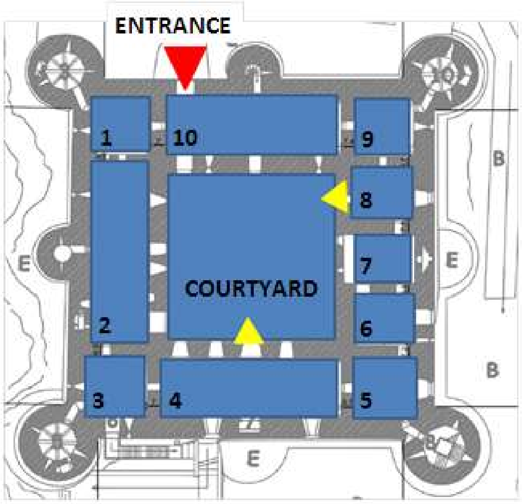
3.1 Case study 1: the Ursino Castle Museum

The Ursino Castle Museum is located in Catania (Sicily, Italy) and consists of 10 rooms located around a central courtyard. The main entrance, represented with a red arrow in Figure 5a, is the only emergency exit that allows exiting from the castle. The other two emergency exits, depicted in yellow, allow the access to the courtyard. Three possible scenarios of explosion inside the museum have been simulated and for each of them the probability of death, injuries and rupture eardrums are calculated. A range of probability of survival is established using the *survivability contours* of given diameters.

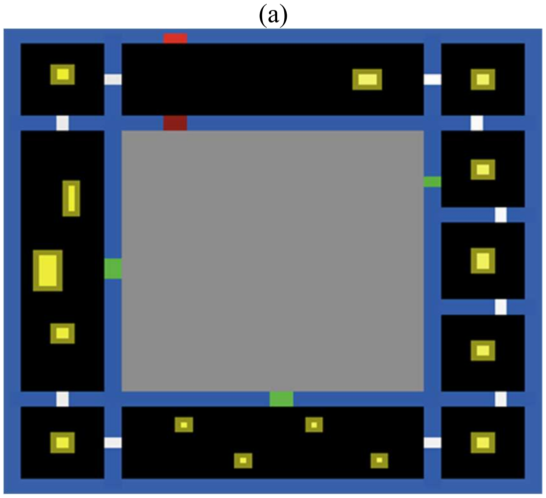
Many agent-based platforms are available in literature and after a careful comparison, the sofware NetLogo has been selected (Wilensky, 1999). Figure 5b describes the NetLogo ABM where the geometry of the structure is shown.

Three scenarios have been selected. In the first one, an explosion in the middle of the fourth room is simulated (Figure 6a). In the second one, the blast is located in the 10th room, near the emergency exit (Figure 6b). The third scenario simulates the worst configuration, in terms of dead and injured agents, because of the occurrence of two consequential explosions. As shown in Figure 6c, the first blast occurs in the room 2 and the second in the room 4.

The number of injuries and deaths is determined using the information provided by the U.S. Department of Army, Navy and Air Force (TM5-1300, 1990; Dalton et al., 2008). For each scenario, a survivability contour plot is calculated (see legend in Figure 6). Within each contour field, a range of probability of survival is established. Figure 7 shows the partial eardrum rupture areas for the considered emergency scenarios as side effect of the selected explosions.

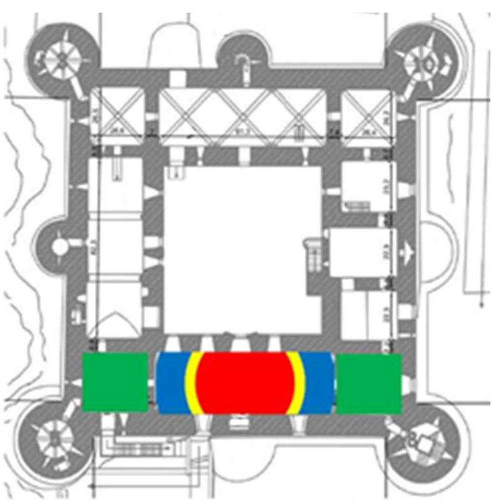


(a)

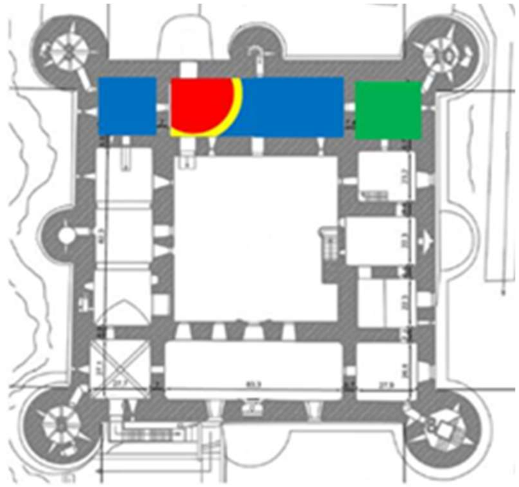


(b)

Figure 5. Plan view of the castle (a). NetLogo ABM scheme (b).



(a)



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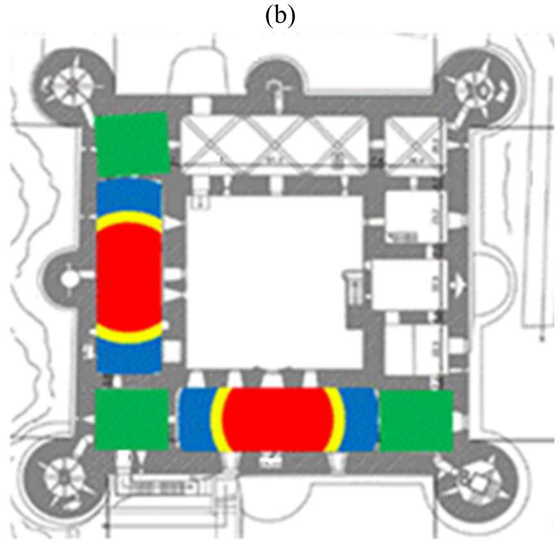
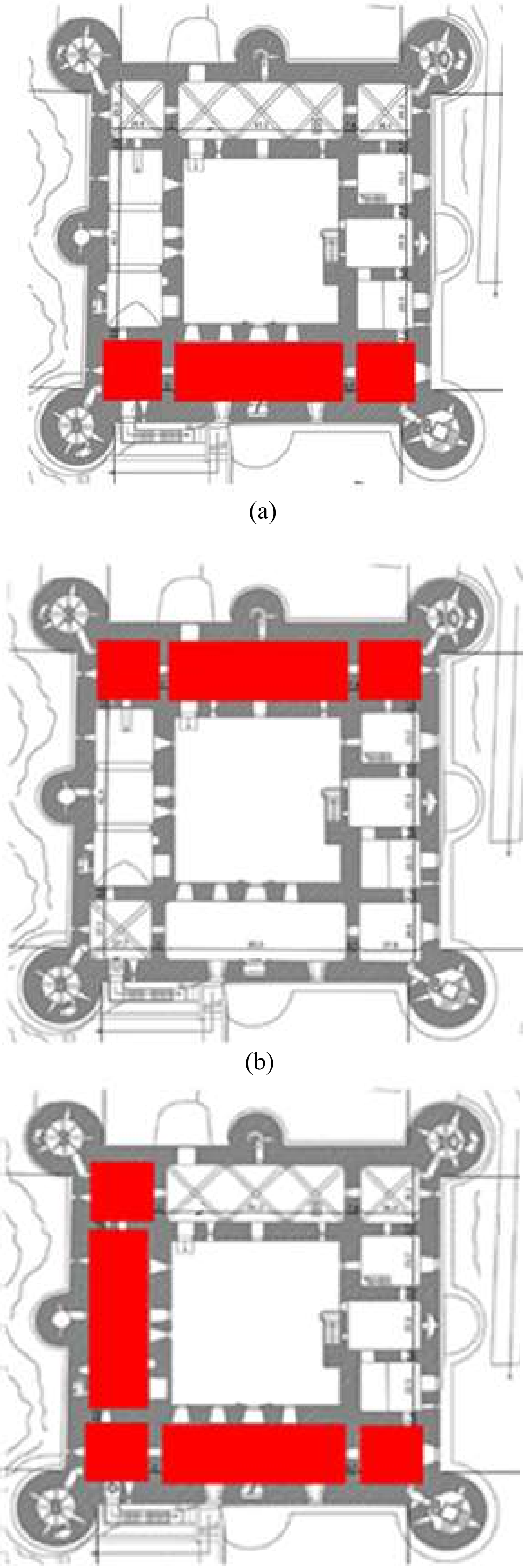


(c)

Legend	Survivability Contours	Diameter
	≤1% Survivability	48-ft
	>1% Survivability & ≤ 50% Survivability	57-ft
	>50% Survivability & ≤ 99% Survivability	83-ft
	>99% Survivability (i.e., threshold)	

Figure 6. Museum's plan with explosion positions. Scenarios 1-3 (a-c).



(a)

(b)

(c)

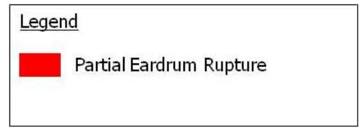


Figure 7. Museum's plan with partial eardrum rupture area. Scenarios 1-3 (a-c).

After the explosion, the probability to survive for each agent varies according to the survivability contours frequencies. For example in the red contours in Figure 6, the probability to survive is only 1%, that correspond to one agent out of the 100 randomly generated.

In the next contour (yellow), if the number is between 1 and 50 the agent is strictly injured, otherwise the agent does not survive. Instead in the blue contour the surviving agents are between 50% and 99% of the cases and the agents who survive are injured with broken bones and burns. The last contour has 99% of survivors with eardrum rupture, resulting in loss of orientation and partial loss of balance. Thus, each scenario holds proper survivability contours with relative diameters. In detail, the agents severly injured are not able to move. The Broken Bones and Burns Injured agents (BBI) are able to evacuate slower than the others, but if they are helped by other agents, they can improve their evacuation speed. The agents that suffer eardrum rupture due to high pressure wave are disoriented.

As explained in Section 2, three models (base, static and dynamic leader-follower behavior) are built. In all the simulations the normal phase lasts until the agents (180) appear in the model and then the emergency phase starts.

The walking speed v of each agent follows the rules below:

- Not injured agents in emergency: v=1.5 m/s.
- Not injured agents in normal phase: v=1 m/s.
- Agents with eardrum rupture walk unsteadily at a speed of v=1 m/s.
- Assisted injured agents: v=0.6 m/s.
- Agents with broken bones / burns: v=0.3 m/s.

The number of persons for squared meter just before the blast in the museum is 0.2 per/m^2, that is lower than 0.54 (Fruin 1971, Peacock et al. 2011, Weidmann et al. 2012) which is the maximum limit below which the walking speed is not influenced by the crowd density. Details on the computational flow are given in Appendix B with some screenshots of the simulations at different time steps.

3.2 Case study 2: the Gare de Lyon metro platform (blast)

The second case study is a platform of the Gare de Lyon metro platform that is a node of the Paris Metrò infrastructure, a large subway that comprises lines 1 and 14 and has a simple rectangular geometry of 142×18m (Figure 8a). The access stairs to the platform are located at the two ends. The platform has automatic screen doors all along the lateral sides of the platform, so in total there are 14 double doors, 1.5m large on each side. In the subway station, three explosions scenarios have been simulated. In the scenario 1, 2 and 3 two bombs are placed respectively at 60, 40 and 20 meters away from the emergency exits (Figures 8b-d).

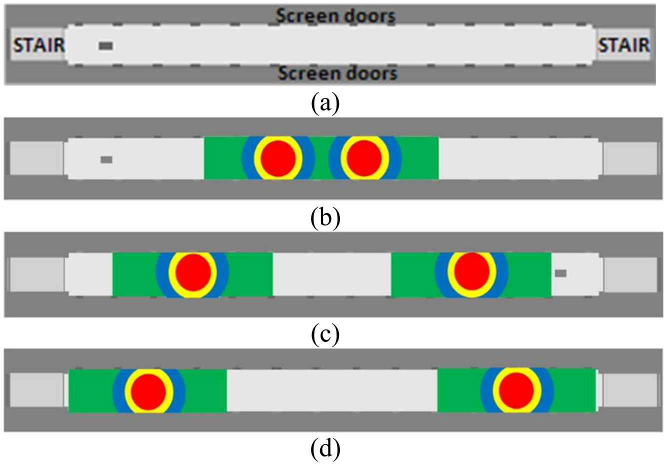


Figure 8. Platform of the Gare de Lyon (a). Blast scenarios 1-3: 60 m (b), 40 m (c), 20 m (d) away from the emergency exits.

As in the previous case study, two phases are considered in the simulations: the normal phase and the emergency one that starts after the occurrence of the blasts with the same number of agents. The normal phase lasts until the agents appear in the model and then the emergency phase starts. It allows deepening the problem within a Monte Carlo approach and finding reasonable results without excessively expanding the computational time. The number of persons for squared meter just before the blast in the platform is 0.07 per/m^2.

The ABM evacuation model has been implemented according with Larcher et. al (2011), where the effects of an explosion inside rail systems are investigated. The fluid-structure interaction model has been employed to compute the response and the failure of the structure, as well as the probabilities of death and eardrum rupture in the metro line station and inside the train.

3.3 Blast damage to buildings

In the last decades several methods have been proposed to determine the explosion wave properties and the blast load parameters. In this study, the blast load parameters required in the structural analyses have been selected by the U.S. Army Technical Manual (TM5-1300 1990).

The magnitude and the distribution of the blast load are function of the energy released by detonation, the weight of propellant (W_{TNT}), and the distance between the explosion and the target (R). W_{TNT} is expressed as an equivalent weight of trinitrotoluene (TNT), while the blast wave demands have been determined as function of the scaled distance parameter ($Z=R/W^{1/3}$).

In the case studies, W_{TNT} is assumed 45.4kg (100lb). This amount of propellant can cause 1% of probability of survival with a radius of 7.3m (24 ft).

The peak reflected pressures (P_r) and the impulsive forces (i_r) have been determined under the fully confined explosion category (TM5-1300 1990), neglecting the influence of frangibility of windows and doors in the analyses. Then, both the peak pressures as well as the impulses have been amplified and integrated to obtain the total blast load.

An idealized blast overpressure time history (Figure 1) has been used to perform dynamic analysis (Marasco et al., 2017). Assuming an overpressure linear decay, a fictitious duration (t_o) has been established as a function of the reflected pressure (Pr) and the impulse (i_r) on the wall:

$$t_o = 2i_r / P_r \tag{3}$$

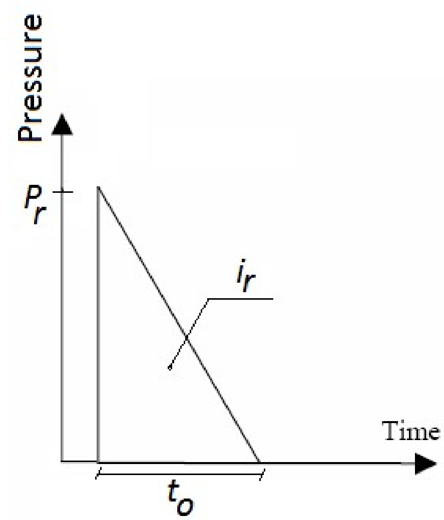


Figure 9. Idealized blast overpressure time history (adopted from TM5-1300-1990)

To conduct the blast analysis, each wall of the museum has been simplified as a single degree-of-freedom (SDOF) system, using an equivalent concentrated mass, stiffness, and force in the midspan of the wall (Marasco et al., 2017).

A brittle behavior for the masonry walls has been assumed, considering its dynamic characteristics under high-velocity impacts (TM5-1300 1990). The thickness of the walls is about 2m (6.7 ft), while its tension strength is assumed to be 5 MPa. The dynamic response of the nearest structural elements (e.g. floor, walls, etc.) have been evaluated for all the considered scenario. The results show that the collapse load of the walls is never reached during the blast analysis. The same analysis has been repeated also for the other case study obtaining similar results. In conclusion with the blast load considered in the scenarios only slight damage is generated in the structural elements of the buildings, therefore the evacuation process is not affected.

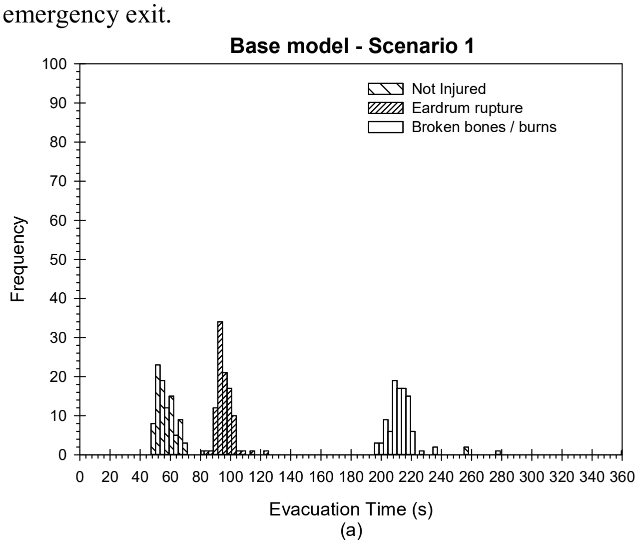
Furthermore, the emergency lights and ventilators are automatically activated after the explosion for improving visibility and removing smokes from the environment.

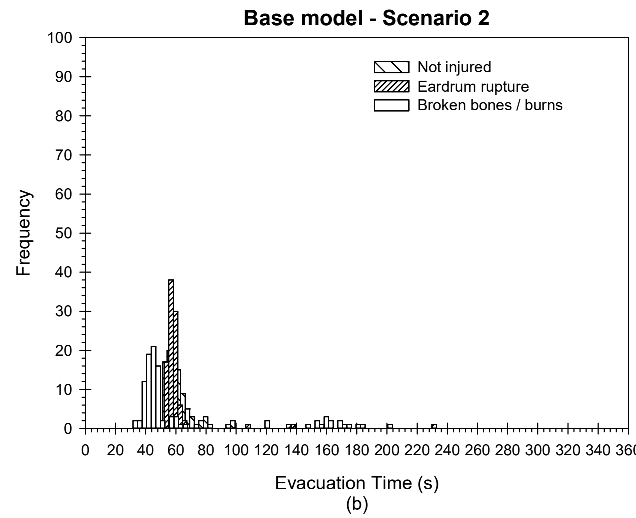
4 RESULTS

The numerical results of a single run are presented in Sections 4.1 and 4.2 in form of histograms for both case studies. In detail, the effect of the human behavior models has been analyzed, but only partial results are shown due to the limited space. Instead in section 4.3 are shown the results of Monte Carlo simulations using multiple runs.

4.1 Case study 1

The results of the Museum *base* model in Figure 10 shows the effect of the different blast positions on the evacuation time. Indeed the evacuation time increases with the distance of the blast from the emergency exit. As a consequence, scenarios 1 and 3 (Figures 10a and 10c) are comparable because the blasts have similar distances from the emergency exit. On the contrary, scenario 2 in Figure 10b presents a lower evacuation time because the bomb is placed near the emergency exit.





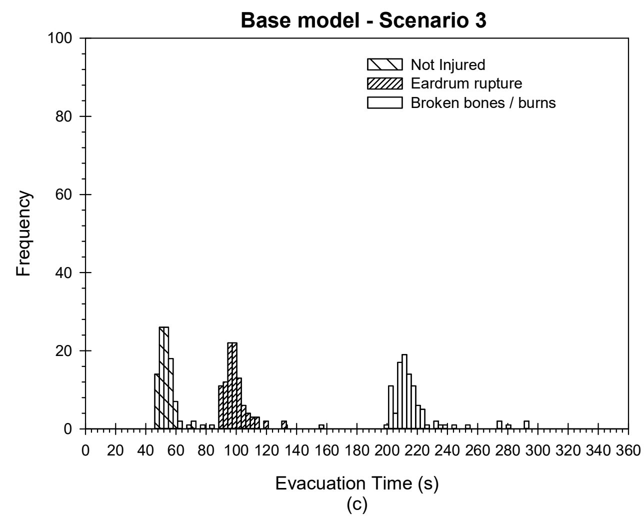


Figure 10. Distribution of evacuation time using the *Base* model vs. different types of agents.

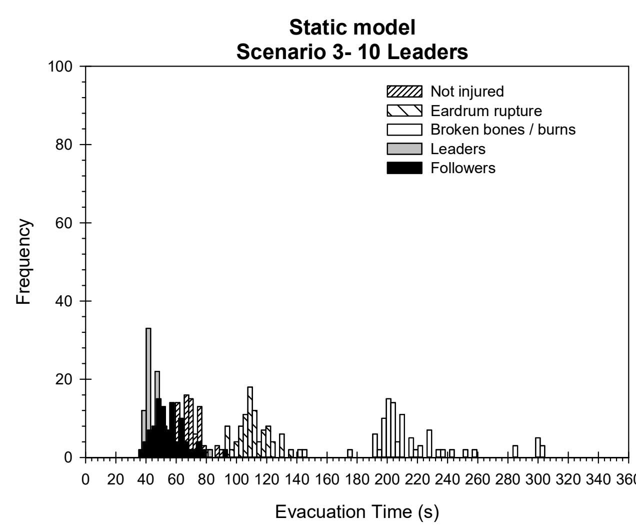


Figure 11. Distribution of evacuation time using the *static leader-follower behavior* model with 10 leaders.

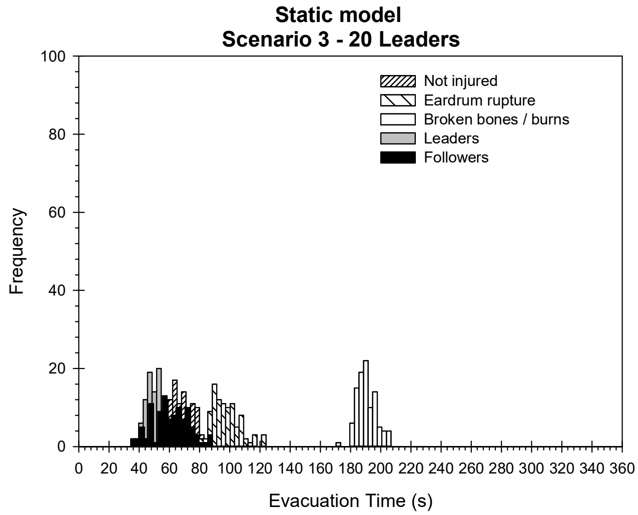


Figure 12. Distribution of evacuation time using the *static leader-follower behavior* model with 20 leaders.

In the assessment of the evacuation time using the *static leader-follower behavior* model, the human behavior plays a key role. Indeed, in the museum that is a intricate environment, the emergency exit are not always visible, so the agents tend to follow a leader. On the contrary, when the emergency exits are visible, e.g in a simple geometric environment, such as the rectangular one without obstacles, the agents do not need to follow the leaders because they evacuate directly through the closest emergency exit.

The results for the scenario 3 in Figure 11 (*static leader-follower behavior* model with 10 leaders) show that the evacuation time of the followers is lower than the injured agents with eardrum rupture and of the not injured agents. Nevertheless, increasing the number of leaders to 20 has a negligible effect as shown in Figure 12.

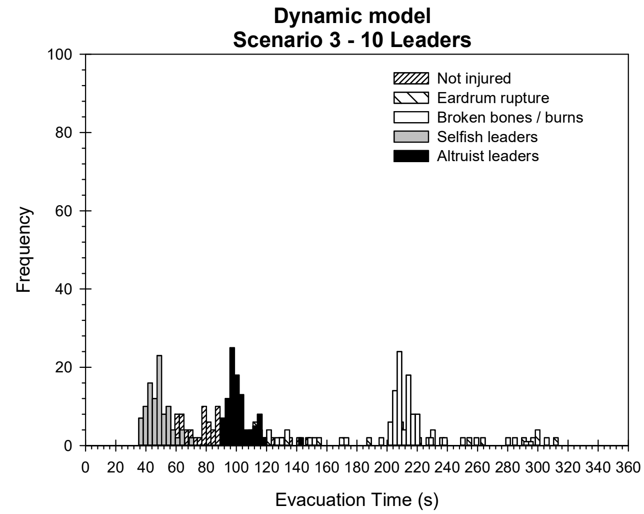


Figure 13. Distribution of evacuation time using the *dynamic leader-follower behavior* model with 10 leaders.

Figure 13 reports the outcomes of the simulations with the *dynamic leader-follower behavior* model for the same scenario 3, including 10 leaders and altruism behavior. The comparison of the results of the dynamic model (Figure 13) with the static model (Figure 11) shows that the altruist behavior does not have a significant impact on the evacuation time.

4.2 Case study 2

Also in this case study (the train platform) the evacuation time is proportional to the distance between the explosions and the emergency exits. Furthermore, the agents that mostly influence the evacuation time are the BBI ones due to their lower evacuation speed. Figure 14 depicts the scenario 1 of the metro platform *base model* where the highest evacuation time is experienced.

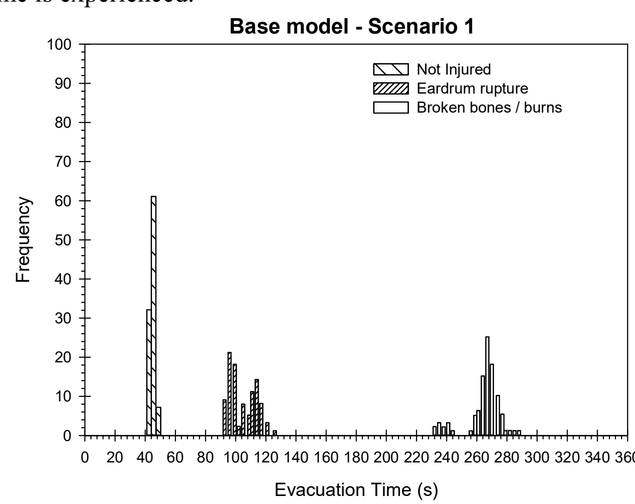


Figure 14. Distribution of evacuation time using the *Base* model vs. different types of agents.

The outcomes of the *static leader-follower behavior* model are depicted in Figure 15 for the same scenario 1 showing negligible differences with respect to the *base* model in Figure 14. According to the simulations, the broken-bones injured agents are the last group that evacuate the area. A modified *static leader-follower behavior* model has been developed by including a new agent category called *guardians*. Their duty comprises the evacuation assistance of injured agents (Figure 16). It is important to clarify that all the simulations do not end until all people are rescued.

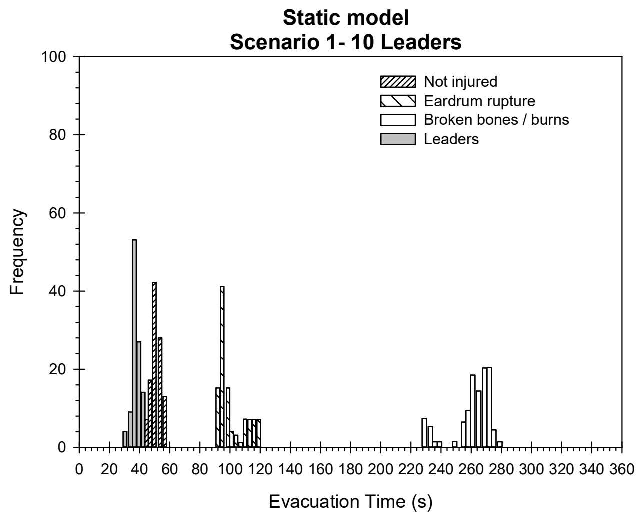


Figure 15. Distribution of evacuation time using the *static leader-follower behavior* model with 10 leaders without guardians help.

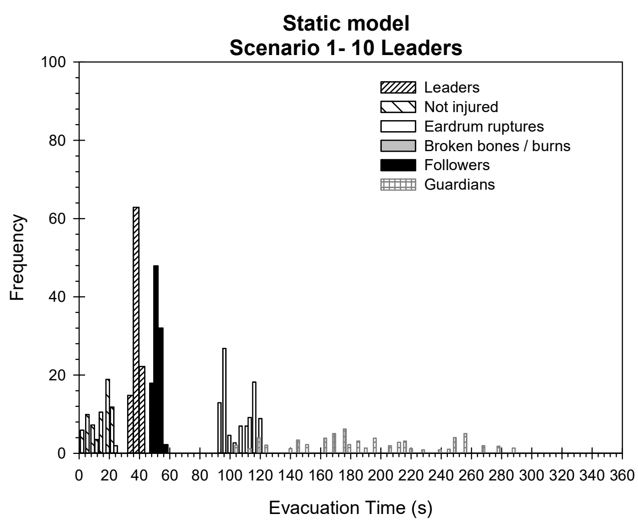


Figure 16. Distribution of evacuation time using the *static leader-follower behavior* model with 10 leaders with guardians help.

Figure 17 shows the results with double the number of leaders with respect to Figure 16. Small differences in terms of evacuation time can be observed between the two cases. Increasing the number of leaders, the evacuation time slight increases because the *guardians* and the *leaders* take care of others and return to help other people until all agents are rescued.

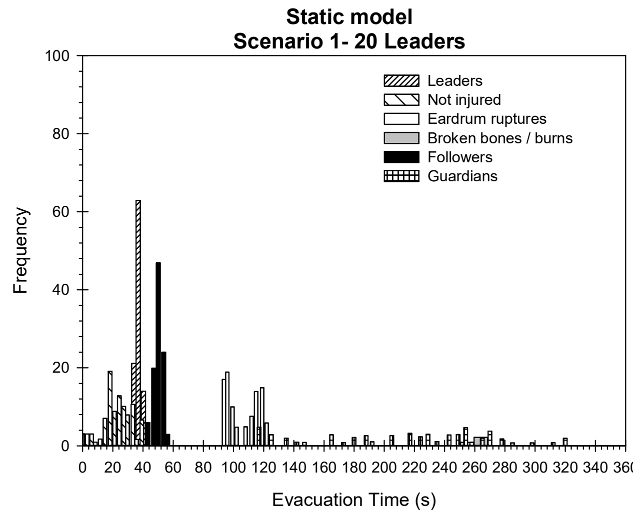


Figure 17. Distribution of evacuation time using the *static leader-follower behavior* model with 20 leaders with guardians help.

The same trend can be observed also in the *dynamic leader-follower behavior* model. The simple regular geometry of the train platform allows all agents to see the emergency exits. So, there is no differences between the two models because all agents move towards the emergency exits without following any other agent.

In Figure 18 the dynamic leader-follower behavior model is presented. The results show that the altruism effect is negligible for scenario 1, while for the other scenarios it has only a limited impact (not shown). The reason is because the injured agents are concentrated in the central part of the platform while the others are moving toward the exits without meeting any injured agents on the way.

Figure 19 shows that doubling the number of leaders for scenario 1, the evacuation time does not change with respect to Figure 18, as in the *static* model.

Guardians have been also included in the *dynamic* model to develop a more realistic evacuation process (Figure 20). Accordingly, with previous observations, an increase in the evacuation time can be observed. Furthermore, it has been noted how the evacuation time depends on the number of *guardians*. A lower number of *guardians* might increase the evacuation time, because they need to do several trips to rescue all the injured agents. Instead, if the number of *guardians* is increased, the evacuation time is usually reduced.

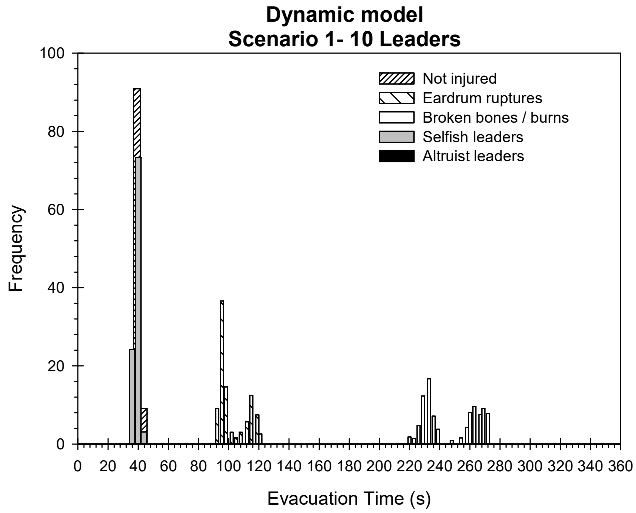


Figure 18. Distribution of evacuation time using the *dynamic leader-follower behavior* model with 10 leaders without guardians help.

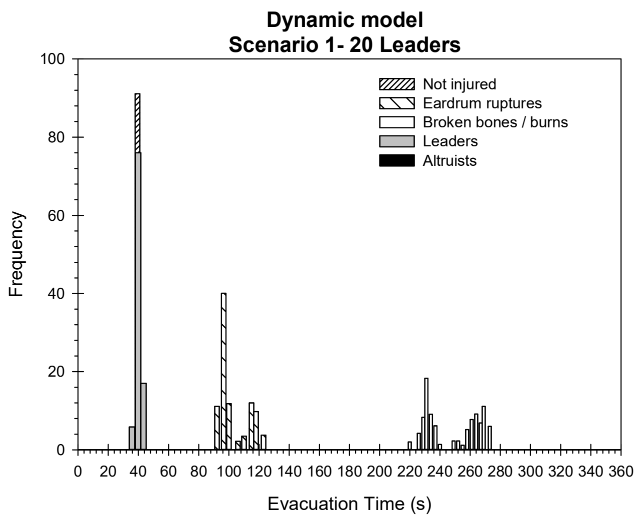


Figure 19. Distribution of evacuation time using the *dynamic leader-follower behavior* model with 20 leaders without guardians help.

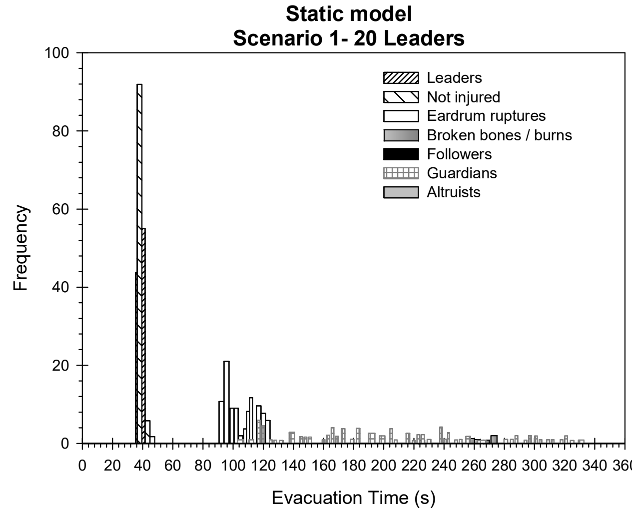


Figure 20. Distribution of evacuation time using the *dynamic leader-follower behavior* model with 20 leaders with guardians help.

4.3 Models validation

In order to validate the models in sections 4.1 and 4.2 existing methodologies from literature have been considered. For example, Ronchi et al. (2013) proposed a methodology for the validation of the evacuation models based on a list of trial tests. Similarly, Mashhadawi (2016) defined a set of functionalities of an evacuation model to simulate pedestrians' movement using benchmark tests. Even if, such references are focused on fire evacuation, quantitative details on pedestrian motion during emergencies can be extrapolated for the aims of validating the present study. After a preliminary assessment the verification tests by Ronchi et al (2013) have been selected. In detail, *pre-evacuation time test* and *movement tests* have been used to validate the proposed ABM models.

4.4 General remarks

For each case study (the museum and the train platform), for each model (*base*, *static* and *dynamic leader-follower behavior*) and for each scenario (scenario 1, 2 and 3), one hundred simulations have been processed within a Monte Carlo approach. The method allows having a wide range of results for each case, so general outcomes can be identified, as discussed in this section.

The leader-follower behavior model is more relevant to simulate reality in a complex geometry like a museum with respect to a simple geometry like the train platform. In fact, in a simple rectangular geometry, where the emergency exits are clearly visible, agents evacuate by them self. On the contrary, in a complex geometry as the museum one agent tends to follow the leaders.

The explosions cause deaths and injured agents. The BBI injured agents may evacuate but slower than the others. If BBI agents are helped by others, the equation speed is improved. However, they are the slowest agents and the last ones to reach the emergency exits. So, they affect the final evacuation time of the simulation.

Figure 21 reports the evacuation time vs the number of BBI agents for *static* and *dynamic* models for the train platform case study. The trend of the *static* model is linear because the agents follow static rules and the total evacuation time depends only on the last BBI agent who reach the emergency exits. Instead, in the *dynamic* models, the evacuation time is always lower regardless the number of BBI agents.

In a complex geometry such as a museum, the evacuation time (Figure 22) has a different trend with respect to simpler geometry (Figure 21). In fact, the *static* model has the lowest evacuation time. Instead, in the *dynamic* models the evacuation time increases with the number of BBI agents. Thus, the altruism in a complex geometry increases the evacuation time with respect to the static *model*.

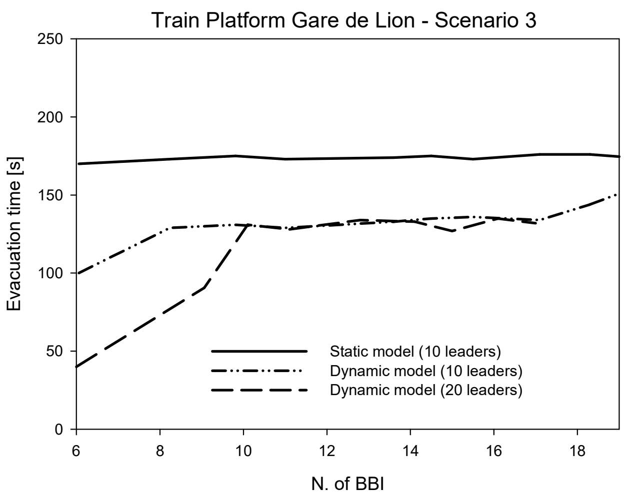


Figure 21. Comparison among the *static* and the *dynamic leader-follower behavior* models with 10 and 20 leaders for the train station.

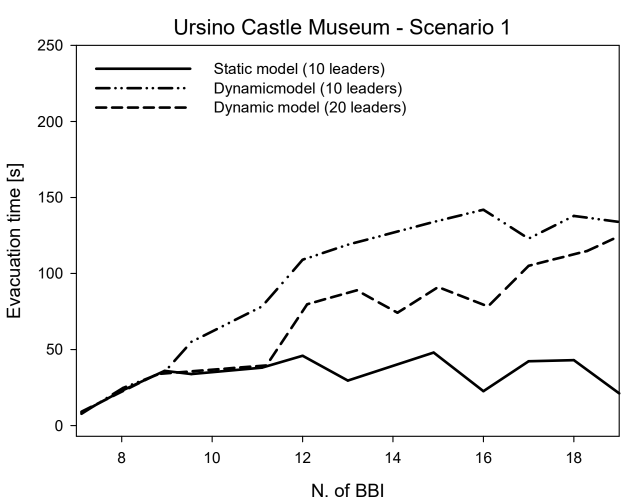


Figure 22. Comparison among the *static* and the *dynamic leader-follower behavior* models with 10 and 20 leaders for the museum.

5 CONCLUSIONS

In this work, a human behavior model has been proposed to describe emergency evacuations after extreme events such as blasts. The proposed model has been implemented within an ABM framework and tested on two different case studies: a museum and an underground train platform.

For both case studies three model have been tested. The *base model* that is characterized by a set of static rules (e.g. each agent evacuates towards the emergency exit, etc.). The *static leader follower-behavior* model that introduces the leader-follower behavior. Instead, in the *dynamic leader follower-behavior* the agent decides whether to follow or not a leader using the Belief-Desire-Intention modelling framework.

From the analyses the following conclusions are obtained.

- The agent's behavior is affected by the complexity of the environment. E.g., in the train platform where the emergency exits are clearly and always visible, the leader-follower dynamics is not triggered due to agents evacuate by their own. Instead, in more complex geometries like the museum, the leader-follower behavior is essential because the emergency exits are not always visible and, consequently, the evacuation path cannot be recognized clearly.
- The altruism behavior is determinant in the exact estimation of the evacuation time that depends on the environment complexity. For example, in the platform case study, the altruism slightly reduces the evacuation time because the injured agents are concentrated in the central part of the platform while the others are moving toward the exits without meeting any injured agents on the way. On the contrary, in a complex geometry such as the Ursino Castle Museum, the evacuation time of leaders (*static* models) with respect to altruist leaders (*dynamic* models) is increased. Furthermore, the increment of the evacuation time results proportional with the number of seriously injured agents.
- Thus, in both case studies, at different levels, when the human behavior is not implemented (*static* model), with respect to the situations when it is (*dynamic* model), the evacuation time is reduced.

With respect to the model assumptions, the proposed approach that includes the human behavior allows to simulate the effect of emotions, irrational behavior and altruism in the evacuation scenarios using stated preference surveys. However, further research is needed by including other aspects of the human behavior (kingship, age, panic etc.) and by considering new details in the simulation

environment, in the evacuation process and in the simulation of the crowd behavior.
The development of the proposed methodology could provide decision support tools for both the designers and policy makers in the decision-making process.

ACKNOWLEDGEMENTS

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APPENDIX A

Figure A1 depicts the questionnaire that is developed in Adobe FormsCentral® and distributed as a submission-enable PDF form or a web form. The response options are close-ended questions mutually exclusive. Different types of response scales are distinguished:

- Ordinal-polytomous, where the respondent has more than two options (e.g. Very unlikely, Unlikely, Neutral, etc.)
- Continuous, where the answers are presented in a continuous scale (e.g. score 1-5)

The proposed survey was filled by 137 people. Their age ranges between 15 and 75 years old, equally distributed among all educational levels and sex.

Before filling out the survey, a video clip with real explosions is shown to the interviewees, to identify themselves in the emergency context and get a more reliable feedback. Furthermore, the subjects are informed about the reason and the purpose of the research study.

The emergency scenarios are presented in the second-person singular, each followed by a series of questions asking the participant to imagine themselves in the scenario. In fact, several survey studies have demonstrated the feasibility of this design in measuring respondents’ behavior from different aspects proposed by TPB, such intention, attitude, subjective norm and perceived behavior control.

The survey allows firstly to assess the percentage of leaders and followers on a sample of individuals. Then, in order to evaluate the behavior as a function of different boundary conditions, it examines how agents (leaders or followers) would behave if during the evacuation they see an injured or another agent who needs help.

Usually, in this type of questionnaires that investigate the human behavior, the most frequent issue that can affect the results is the *social desirability bias* phenomenon (Phillips & Clancy 1972a, 1972b). It is tendency of survey respondents to answer questions in a way that will be viewed favorably by others, avoiding socially undesirable traits and over-reporting "good behaviors" to achieve social approval. In the survey, a tendency of respondents to over-report "good behavior" in response to questions "How likely is that you would decide to stop if you see someone who needs help?" has been highlighted. Consequently, the assumption that injured people do not help others injured has been made.

Questions are created to split the sample of interviewees in categories (e.g. *leaders* and *followers*). For example, the potential leaders are identified through *Questions 1 and 2* (Figure A1). Indeed, a leader tends to evacuate by its own (*Question 1*, *likely/very likely*) and has a lower tendency to follow a group of people that is evacuating (*Question 2, not/definitively not*). In addition, *Question 15* is added at the end of the questionnaire to verify that the interviewee does not contradict himself.

PEER

Emergency Scenario Survey

Informed Content
You are being invited to take part in a research study. The information in this form is provided to help you decide whether or not you want to take part.

What is the purpose of this research study?
The objective of this project is to use an emergency scenario survey to analyze how people evaluate emergencies situations, to develop an accurate simulation model of an emergency evacuation, such as from a explosion, taking into account human behavior.

Will the information that is obtained from me be kept confidential?
No personal information of yours will be collected. The only persons who will know that you participated in this study will be the research team members; specifically, the Principal Investigators and the advisor. Your responses will be confidential. You will not be identified in any reports or publications resulting from the study.

May I change my mind about participating?
Your participation in this study is voluntary. You may decide to not begin or to stop the study at any time. Also any new information discovered about the research will be provided to you.

Whom can I contact for additional information?
You can obtain further information about the research or to voice concerns or complaints about the research by calling the Principal Investigators.

Noticed : to fill out the questionnaire you must be connected to Internet

Gender	Age	Education
○ male	○ 15-30	○ elementary school
○ female	○ 31-45	○ middle school
	○ 46-60	○ high school
	○ 61-80	○ bachelor degree
		○ master degree or higher

We ask you to watch a video clicking on the link below before filling the survey

VIDEO

(a)

As shown in Figure 1 below, you are in a museum and you are heading in the direction of the green arrow.
If a explosion occurs and this blast has caused death, injured and people with eardrum rupture (this means temporary hearing loss and disorientation).
After the blast you must evacuate to a safe area. Your options are to find an emergency exit yourself or to join a group of people who are also running away.

Assuming that
- You are not injured and without eardrum rupture
- You are alone without any relative or friend
- You do not see any emergency exit

Figure 1. Depicts of a museum room

Question 1

	Very unlikely	Unlikely	Neutral	Likely	Very Likely
How likely is that you would decide to evacuate on your own?	○	○	○	○	○

Question 2

	Definitely	Probably	Not sure	Probably not	Definitely not
Would you decide to join a group of people who are running away from the blast?	○	○	○	○	○

(b)

Question 3

	Very unlikely	Unlikely	Neutral	Likely	Very Likely
How likely is that you would decide to stop if you see someone who needs help?	○	○	○	○	○

Question 4

	1	2	3	4	5
How likely is, from 1 to 5, that you would decide to aid a severely injured person?	○	○	○	○	○

Assuming that
- You are alone without any relative or friend
- You do not see any emergency exit
- **You are injured** (this means that you have a eardrum rupture and burns in the body but you can walk by yourself)

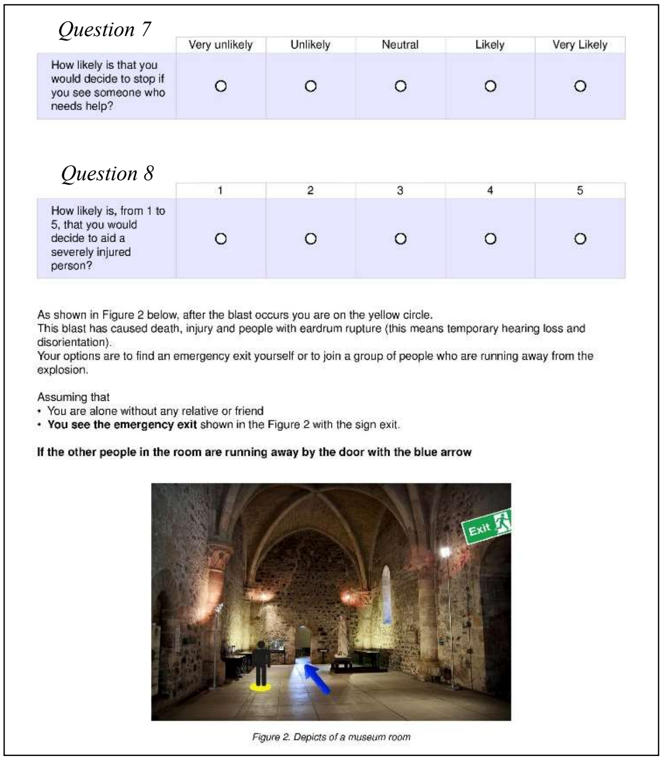
Question 5

	Definitely	Probably	Not sure	Probably not	Definitely not
Would you decide to evacuate on your own?	○	○	○	○	○

Question 6

	Very unlikely	Unlikely	Neutral	Likely	Very Likely
How likely is that you would decide to join a group of people who are running from the blast?	○	○	○	○	○

(c)



Question 7

	Very unlikely	Unlikely	Neutral	Likely	Very Likely
How likely is that you would decide to stop if you see someone who needs help?	○	○	○	○	○

Question 8

	1	2	3	4	5
How likely is, from 1 to 5, that you would decide to aid a severely injured person?	○	○	○	○	○

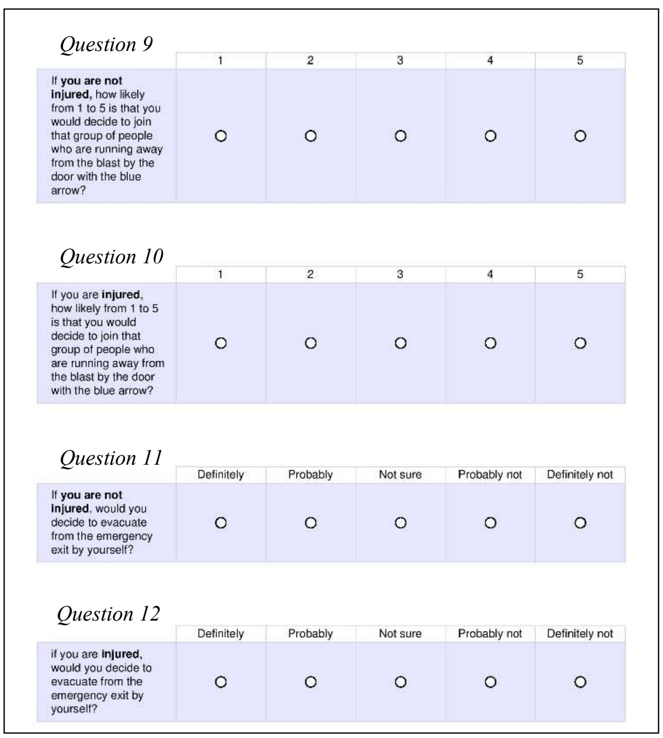
As shown in Figure 2 below, after the blast occurs you are on the yellow circle.
This blast has caused death, injury and people with eardrum rupture (this means temporary hearing loss and disorientation).
Your options are to find an emergency exit yourself or to join a group of people who are running away from the explosion.

Assuming that
- You are alone without any relative or friend
- **You see the emergency exit** shown in the Figure 2 with the sign exit.

If the other people in the room are running away by the door with the blue arrow

Figure 2. Depicts of a museum room

(d)



Question 9

	1	2	3	4	5
If **you are not injured,** how likely from 1 to 5 is that you would decide to join that group of people who are running away from the blast by the door with the blue arrow?	○	○	○	○	○

Question 10

	1	2	3	4	5
If you are **injured**, how likely from 1 to 5 is that you would decide to join that group of people who are running away from the blast by the door with the blue arrow?	○	○	○	○	○

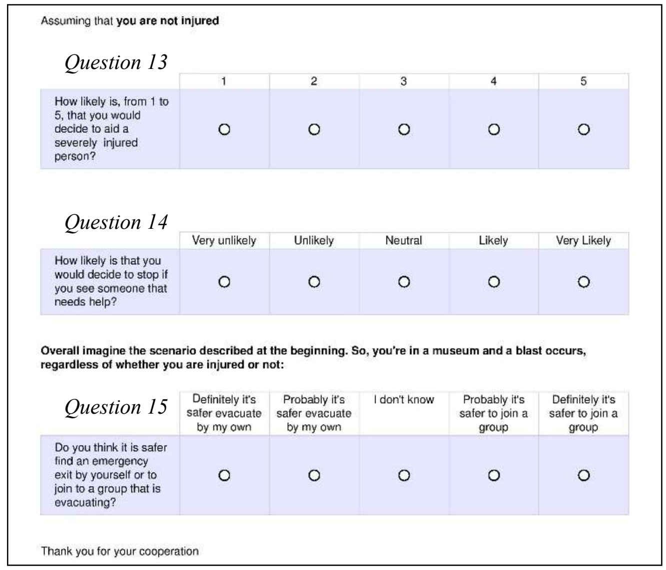
Question 11

	Definitely	Probably	Not sure	Probably not	Definitely not
If **you are not injured**, would you decide to evacuate from the emergency exit by yourself?	○	○	○	○	○

Question 12

	Definitely	Probably	Not sure	Probably not	Definitely not
if you are **injured**, would you decide to evacuate from the emergency exit by yourself?	○	○	○	○	○

(e)



Assuming that **you are not injured**

Question 13

	1	2	3	4	5
How likely is, from 1 to 5, that you would decide to aid a severely injured person?	○	○	○	○	○

Question 14

	Very unlikely	Unlikely	Neutral	Likely	Very Likely
How likely is that you would decide to stop if you see someone that needs help?	○	○	○	○	○

Overall imagine the scenario described at the beginning. So, you're in a museum and a blast occurs, regardless of whether you are injured or not:

Question 15

	Definitely it's safer evacuate by my own	Probably it's safer evacuate by my own	I don't know	Probably it's safer to join a group	Definitely it's safer to join a group
Do you think it is safer find an emergency exit by yourself or to join a group that is evacuating?	○	○	○	○	○

Thank you for your cooperation

(f)

Figure A1. Questionnaire: pages 1-6 (a-f).

Then, the results of the survey are used to derive the weight vectors *W*, the preference vector *P*, and the *M* matrix.

In order to understand the detailed procedure to determine the parameters of the human behavior model first it is necessary to categorize the agents after the explosions in two groups:

- the *leader* that accepts a higher risk and is determined to move towards the emergency exit.
- The *follower* that moves together with a group of people or a leader.

In addition, after the explosion, three attributes (n=3) corresponding to the environment perceptions that affect the agents' decision are considered:

1. Health status *S* (injured/not injured).
2. Location of the Emergency Exit *E* (see the emergency exit/do not see the emergency exit).
3. Presence of injured agents *I* (meet/do not meet an injured one).

The attributes are combined in eight possible agent conditions (2^3=8) within the simulation environment.

Table A1 lists all the eight possible agents' conditions after the explosion and the corresponding questions from the survey that allow defining the agent behavior during the ABM simulation.

Table A1

Possible agent conditions and survey questions (Fig. A1).

AGENT CONDITIONS	*QUESTIONS*
S *= NOT INJURED* ***E*** *= DO NOT SEE EMERGENCY EXIT*	***1,2***

I *= DO NOT SEE INJURED*	
S *= NOT INJURED* ***E*** *= DO NOT SEE EMERGENCY EXIT* ***I*** *= SEE INJURED*	***1,2,3***
S *= NOT INJURED* ***E*** *= SEE THE EMERGENCY EXIT* ***I*** *= DO NOT SEE INJURED*	***11,9***
S *= NOT INJURED* ***E*** *= SEE EMERGENCY EXIT* ***I*** *= DO NOT SEE INJURED*	***11,9,13***
S *= INJURED* ***E*** *= DO NOT SEE EMERGENCY EXIT* ***I*** *= DO NOT SEE INJURED*	***5,6***
S *= INJURED* ***E*** *= DO NOT SEE EMERGENCY EXIT* ***I*** *= SEE INJURED*	***5,6,7***
S *= INJURED* ***E*** *= SEE EMERGENCY EXIT* ***I*** *= DO NOT SEE INJURED*	***12,10***
S *= INJURED* ***E*** *= SEE EMERGENCY EXIT* ***I*** *= SEE INJURED*	***12,10,7***

Below is described the procedure to build the vector W defined in Equation (2) for one of the eight agent conditions. Let's assume for example we are in the second agent condition of Table A1 that corresponds to the *follower* category (*k=Follower, q=2^nd^ agent condition*):

$$W_{F2} = \begin{pmatrix} W_{F2S} \\ W_{F2E} \\ W_{F2I} \end{pmatrix} = \begin{pmatrix} Question\ 1 \\ Question\ 2 \\ Question\ 3 \end{pmatrix} \qquad \text{(A1)}$$

For example, *Question 1* is used to define the first element of the vector that consists of a number W_{F2S} ranging within an interval [$W_{F2S.max}$ W_{F2Smin}]. Let's clarify this using the results of the questionnaire. In *Question 1* the answer "*likely/very likely*" has been selected 58 times out of 137 samples. The answer "*Neutral*" has been selected 17 times. Therefore the corresponding upper and lower frequencies are 58/137=0.42 and (58+17)/137= 0.55. Finally, W_{F2S} is selected randomly within the interval [0.42-0.55] (Lee et al. 2008). The same procedure is repeated for all elements of the vector W and for all the 16 options.

The next step considers the value matrix M ($m\times n$) that represents the subjective evaluations (perceptions) of a decision-maker (agent) for each option m on each attribute n. For example, let's assume that an unbiased news is provided through a magazine. The reader has his own subjective preliminary evaluation (matrix M_1) about the news. However, the value matrix may change dynamically through the time, because of the environment and the logic sense of the agent, so a new matrix M_2 is created (Lee et al. 2008). However, in the present study the variability of M is not considered because during the emergency the subject's judgement is assumed to not change.

A backward process is used to calibrate the M matrix adopting Equation (1). First, the weight vectors W are defined assuming a normal distribution within the intervals and selecting the corresponding mean values (Busemeyer, J. & Diederich, 2002). Then the temporary values of the preferences P are obtained from the questionnaires and used as input in the backward process to determine the M matrix. The Contrast Matrix C is also defined through the procedure at section 2.3. The backward process on Equation 1 can be applied considering: e.g. at time t=0 preference P=0, so SP=0, resulting:

$$P = CMW \qquad \text{(A2)}$$

Therefore, matrix M is the only unknown and can be derived for implementation.

APPENDIX B

The methodology is implemented in an ABM open source platform called NetLogo that is multi-agent programmable modeling environment. The software is suited for modeling complex systems developing over time. Specific routines have been developed to adapt the agent's dynamics to the motion inside a confined environment. In detail, the proposed model is a behavioral one, because each agent moves toward specific goals, performing decision-making based on its own preferences, on the conditions of the building and on the location (and behavior) of other agents. The crowd behavior has been modelled using a repulsive force between agents, so each agent "emit" a kind of force that other agents detect and try to avoid (Gipps and Marksjo, 1985). This force modifies the speed of the agents near the exit and in narrow places where the agents get closer.

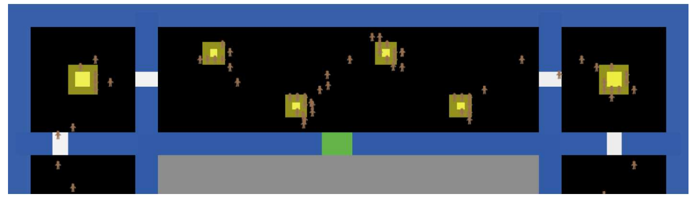
A network grid structure has been used where each cell allows for only one occupant at a time. The model can track the movements of agents during the simulations. Each agent is a-priori not aware of the building's emergency exit paths, except from the main entrance, and does not have any a-priori information on the optimal route to follow in case of emergency. The human behavior model (e.g. dynamic model) in the simulations is implemented in Matlab and linked to the ABM model. At each simulation step, the agent preferences are computed accordingly with Equation (1) and transferred to the virtual world driving the agents' behavior. The inclusion of the human behavior model increases the computational time of the analyses, but if they are not considered, the evacuation time is usually underestimated. However, the higher computational demand in the simulation can be reduced using parallel computing. Below, the standard Matlab function for *not injured follower*, is reported as an example.

Matlab function - not injured follower

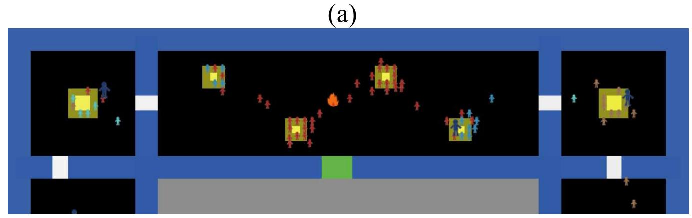
```
function FOLLOWERNIdyn(iE,iI,iColor)
nSubj=1;
nDeliberTime=150;
S=[0.8 -0.01 -0.01; -0.01 0.8 -0.01 ; -
0.01 -0.01 0.8];
```

```
C=[1 -0.5 -0.5; -0.5 1 -0.5; -0.5 -0.5 1
];
MF1=[13.3 -2.4 3.8; 16.4 -3.8 3.1; 15.2
-3.8 3.1 ];
MF2=[15.2 -8.7 3.8; 20 -10.7 3.1; 21 -
10.7 3.1 ];
MF3=[16.6 -15.1 10; 14.5 -13.1 10; 13.2
-11.8 10 ];
MF4=[5.3 -15 10; 3.6 -13 10; 3 -11.8 10
];
W=[w1;w2;w3]
P=[pca;pcb;pcc];
Pa1=0;
Pb1=0;
Pc1=0;
  for n = 1:nSubj
    if  (iE == 1)
      if (iI ==1)
      P(:,n)=S*P(:,n) + C*MF4*WF4
      else
      P(:,n)=S*P(:,n) + C*MF3*WF3
      end
    else
      if (iI ==1)
      P(:,n)=S*P(:,n) + C*MF2*WF2
      else
      P(:,n)=S*P(:,n) + C*MF1*WF1
      end
    end
  end
assignin('caller','pa',P(1,n))
assignin('caller','pb',P(2,n))
assignin('caller','pc',P(3,n))
 if rem(m, 10) == 0
   for n = 1:nSubj
     if P(1,n) > P(2,n) && P(1,n) > P(3,n)
     Pa1 = Pa1 + 1;
     elseif P(1,n)<P(2,n)&&P(3,n)<P(2,n)
     Pb1 = Pb1 +1;
       else
       Pc1 = Pc1 +1;
       end
     end
   Pa=(Pa1*10)/m; Pb=(Pb1*10)/m;
  Pc = (Pc1*10) / m;
 End
```

Figure B1 depicts the simulation at different intervals. Figure B1a report the normal phase in some rooms of the Museum while Figure B1b the explosion.



(a)



(b)

Figure B1. Ursino Castle Museum. Normal phase with agents in good health status (brown agents) (a). Explosion with deaths (red agents), *guardians* (dark blue agents), injured broken bones/burns (blue agents), injured eardrum rupture (light blue agents) (b).