Simulating Collective Evacuations with Social Elements

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Abstract. This work proposes an agent-based evacuation model that incorporates social aspects in the behaviour of the agents and validates it on a benchmark. It aims to fill the gap in this research field with mainly evacuation models without psychological and social factors such as group decision making and other social interactions. The model was compared with the previous model, its new social features were analysed and the model was validated. With the inclusion of social aspects, new patterns emerge organically from the behaviour of each agent as showed in the experiments. Notably, people travelling in groups instead of alone seem to reduce evacuation time and helping behaviour is not too costly for the evacuation time as expected. The model was validated with data from a real scenario and demonstrates acceptable results and the potential to be used in predicting real emergency scenarios. This model will be used by emergency management professionals in emergency prevention.

Keywords: Social contagion · Agents · Model · Evacuation · Simulation

1 Introduction

Preventing incidents in crowded environments involves many aspects such as investigating the effects of environmental factors like the number of doors, their positions, the location of other objects and escape areas. All these factors have a big impact on evacuation time and consequently influence the number of injuries and casualties. There are many details to be considered, some of them are predefined by the design of the building itself, such as stairs, width of exits and existing pillars. Other environmental aspects are organised only hours before an event starts, such as areas for queuing, gates and signs to direct the flow of people. Moreover, there are psychological and social factors that have an effect on the evacuation process as well, such as age, gender, language, being in a rush. To avoid dangerous situations, organisers follow security protocols and make scenario simulations. Simulations are good to indicate security lacks and unpredicted situations. Most of the evacuation simulation tools consider physical characteristics of the environment, ignoring behaviour and personality of people. Some of them consider queues formation, jamming, clogging, fluid movement of crowds and following behaviour [22].

Evacuation simulation models could become more precise by incorporating realistic human behaviours, as currently they do not. Most evacuation simulation models do not incorporate psychological and social factors. Observations of actual emergencies show that people tend to be slow to respond to evacuation alarms (taking up to 10 min) and

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take the familiar route out instead of the nearest exit [1, 7]. Most models simulate people like ‘robots’ taking rational decisions to reach a safe place, avoiding obstacles and suffering the influence of the environment in their speed to escape from a dangerous place. Including psychological and social factors in evacuation simulations could make these models more realistic and better in their predictions to ultimately save more lives.

As part of the EU Horizon 2020 project IMPACT[1], this work will propose and validate an evacuation simulation incorporating social factors, named the IMPACT model. It is a refinement and extension of an initial version of the model proposed in [18]. New features added are: helping behaviour, groups, age and gender. The following social features were refined: familiarity, response time and social contagion. The rest of the paper is organised as follows. Section 2 starts with a short literature review. Next, Sect. 3 introduces the conceptual and formal model with the new features. This is followed by reports of the simulation experiments in Sect. 4 and a summary and discussion in Sect. 5.

2 Related Work

There are many different approaches for computer models of crowd evacuation simulations. Zheng and colleagues describe seven approaches for computer evacuation models: (1) cellular automata, (2) lattice gas, (3) social force, (4) fluid dynamics, (5) agent-based, (6) game theory, (7) animal experiments [22]. Each one of these approaches combines physical aspects with statistics measurements of evacuation flows in diverse types of environments. According to Templeton and colleagues, current crowd simulations don’t include psychological factors and therefore cannot accurately simulate large collective behaviour that has been found in extensive empirical research on crowd events [16]. On the other hand, Santos and Aguirre have reviewed the integration of social and psychological factors incorporated in evacuation simulation models [13]. They describe how social dimensions are incorporated in three evacuation simulation models: FIRESCAP [4], EXODUS[2] [6] and multi-agent simulation for crisis management (MASCM [8]).

MASCM includes social interaction in the way of evacuation leaders. For example, evacuation leaders can communicate ‘please follow me’ and start to walk along the evacuation route or find an evacuee at the distance or wait for the evacuee to approach. Even though leadership is modelled fairly accurate, there is no possibility of simulating the set of group decision-making processes involved in selecting a leader when there is no trained professional/evacuation leader present. Yet in evacuation situations, there are often no official leaders. Also, evacuees in MASCM go to the nearest group, but research suggests that such an action typically involves social factors including the relationship between the evacuees from the start of the evacuation. EXODUS includes 22 social psychological attributes and characteristics for each agent, including age, name, sex, breathing rate, running speed, dead/alive, familiarity with building, agility and patience. Yet, agents in EXODUS cannot have social micro-level interactions that would create

1 http://www.impact-csa.eu/.
2 http://fseg.gre.ac.uk/index.html.

a collective definition of the situation for groups and collective interactions. Other models that Santos and Aguirre reviewed do not model social dimensions, such as group decision making, but focus more on the physical constraints and factors such as walking speed, walkways, stairways etcetera to find the optimal flow of the evacuation process. This work aims to fill this gap in the field of evacuation simulations, by proposing a model that includes social interactions and collective decision making.

3 IMPACT Model

The evacuation dynamics were modelled using an agent-based model with the beliefs-desires-intentions and network-oriented modelling approaches [11, 17]. The first version of the model included physical, psychological and social aspects. Each agent in the simulation has his own characteristics and his behaviour is influenced by environment as well as by other agents around him. Table 1 describes the internal characteristics of each agent and the external influences on them as the initial version [18].

Table 1. Individual agent characteristics in the initial version of the model.

Characteristic	Description
Familiarity	When an agent is familiar, he chooses the nearest exit otherwise, he always evacuates via the main exit
Compliance	The compliance level of each agent can vary between 0 and 1 and has an effect on the agent's desires. In the initial version, the setting was fixed to 0.5 for each agent
Fear	Internal state influenced by external factors and other internal states
Belief of danger	The level of this state directly influences the decision to evacuate or not. It is a combination of fear and external stimuli
Desire walk randomly or evacuate	Depending on the level of Fear and Belief of danger, an agent can have the desire to walk randomly in the environment or to escape
Intention of walk randomly/evacuate	Based on the desires, the agent creates an intention (decision) to perform a certain action with a certain intensity
Speed	Maximum speed of the agent, depending on intensities of the intention. It varies from walking to running. Range: (1.42 m/s, 4.26 m/s)
Express emotion	Expression of fear to other agents within observation distance
Vision radius	Scope of vision of an agent
Fall	Each agent can fall, spending some time before standing up and continuing its path. The chance of falling is based on the number of agents around and the agent's own speed. The more people around the agent, the faster the agent runs and the higher the chance to fall
Observation event (external factor)	Agents who observe dangerous events change their beliefs and immediately start to evacuate
Observation alarm (external factor)	When the alarm sounds, there is a 50% chance for each agent to start to evacuate. (Representing risk-taking, as not all passengers react quickly to a fire alarm [7, 10])
Observation fear (external factor)	Agents can observe other's fear and belief expressions and decide to evacuate without seeing the danger him/herself

The model was implemented in the Netlogo multi-agent language [20]. Figure 1 gives an overview of the conceptual model, showing four agent modules. Individual characteristics influence all other modules. the perceived external stimuli from others (people-people interaction) and from environment (people environment interaction) affects directly the actions in such a way that the patterns simulations emerge organically from the behaviour of each agent and events in the environment.

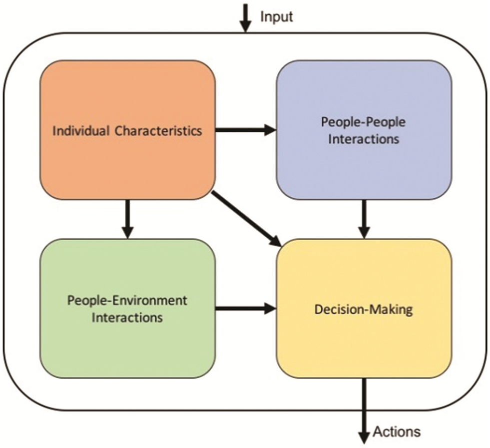

Fig. 1. Agent modules of the IMPACT model.

Comparing the current IMPACT model to the initial one, some characteristics were updated regarding speed, falls and compliance. For all of them, the updates are based on psychological and statistical analyses as described below.

- **Speed:** The walking speeds varied for each demographic group (children, adult males, adult females, elderly males, elderly females) and were based on the observational work of Willis et al. [21], ranging from 1.12 m/s to 1.58 m/s. We calculated running speeds by multiplying the walking speed for each demographic group by three – to account for the luggage, belongings, and clothes that people wear while travelling – to yield speeds between 3.36 m/s and 4.75 m/s. Moreover, a crowd congestion factor was added that reduces the speed according to the number of agents within the same square metre: $\leq$ 4 people (no speed reduction), 5 people (62.5% reduction), 6 people (75%), 7 people (82.5%), 8 people (95%). These speed adjustments were based on research by Still [15], where 8 is the maximum number of people per square metre and 4 the number of people from which speed reduces.
- **Falls:** The number of falls in the initial model seemed unrealistically high during structured simulations. So, we manually tuned the value to a more realistic level by visually inspecting the movement patterns during many different settings. This resulted in a new rule: if there are more than 4 people in the same square metre of the agent and if he is running more than 3 m/s, then there is a 0.5% chance of a fall for each new movement.

- **Compliance:** In the current version, the probability of compliance is based on data from Reininger et al.'s [12] study of gender differences in hurricane evacuation, modified for different age groups using data from Soto et al.'s [14] personality study. The model has 6 compliance values according to the category of the agent: male or female, and child, adult, or elderly. The precise levels can be found in Sect. 2 of [19].

Besides the improvements in speed, falls and compliance that have substantial changes to the outputs of scenario simulations, three new social features were added to the model. These new social factors were chosen by the stakeholders of the IMPACT project to make the model more realistic and effective for emergency prevention/predictions. The current IMPACT model categorises the agents in groups of age and gender. Based on these characteristics the agents have different speed and compliance levels, consequently their fear, belief of danger, express of emotions and desire to walk randomly or evacuate vary more realistically according to the type of agent and in relation to the initial model. Each agent has his own personality, for example, not all female elderly has the same speed, but they vary among a range of possible speeds for that category. The same occurs for the other groups.

As an example, Eq. 1 shows how the desire to evacuate is calculated and how compliance influences this internal state. A logistic function is thereafter used to decide if the intention to evacuate or keep walking randomly is larger. Then, this outcome is multiplied by the desire to evacuate to represent the strength of the intention. In this way, compliance Level has a direct effect on the value of desire to evacuate. The result is a number between (0, 1), whereby 0 means a minimal intention and 1 a maximal intention to evacuate. Each decision and internal state in the model has a formal rule, for lack of space, only the rule to calculate the desire to evacuate is shown below. All formal rules can be found in [19].

$$\begin{aligned}&\text{desire\_evacuate(t)} = \\ &\text{desire\_evacuate(t)} + \eta \cdot \\ &\Big(\Big(compliance \cdot \Big(\max\Big(\omega_{amplifyingevacuation} \cdot \text{belief\_dangerous(t)},\ \omega_{amplifyingevacuation} \cdot \\ &fear(t), \omega_{amplifyingevacuation}\Big)\Big)\Big) - \text{desire\_evacuate(t)}\Big) \cdot \Delta t.\end{aligned} \tag{1}$$

Whereby,

ω = *predefined weights of the tuned model.*
η = *speed factor, defines how smooth or abrupt changes in the calculations happen.*
max = *function that returns the maximum value among the parameters.*

The current IMPACT model also includes group formations. Currently, it supports the most frequent types of groups with 2, 3 and 4 people. Agents in a group always move together with the same speed. The group speed is 40% of the difference between the minimum and maximum speed of group's members, assuming that the slower people in the group can be 'pulled' along faster or children can be carried, but not faster than the average speed of the group. Children are always part of a group, while adults and elderly can both travel alone as in groups. One of the group members is always the leader, the others follow him. However, the leader is constantly influenced by other members of the group since they are close to each other, so if other members express a high level of fear, the leader will increase his level of fear in a re-feed cycle until a stable value is reached that could be enough to make the leader decide to evacuate.

Besides that, helping behaviour was included. An agent can decide to help other people that felt on the floor. That means, the agent stops in front of the fallen agent until it stands up and after that, each agent follows his own path. The decision to help another agent is a statistical combination of gender, age and group identity of the helpers and fallers. For example, if the agent belongs to a group, there is a very high chance that his group members help him [2]. Men are most likely to help others and women, children, and older adults are most likely to receive help [3].

4 Simulation Results

Experimental Design. Simulation experiments with different factors and levels were designed to answer the research questions of this work: (1) Model comparison: does the model have significant differences after the improvements compared to the initial version? (2) Model validation: does the model correspond to reality and in how far? (3) Model simulations: what are the effects of the new features: helping and group formation on the evacuation time? A square (20 × 20 m) layout of a building with two exits (4 metres wide) was chosen to represent a general building layout. All environmental and personal factors such as width of the doors and level of compliance were kept constant among simulations. Only the factors and levels stated in each experimental setup were systematically varied. After inspecting the averages and variances in evacuation time of 100 simulations of a scenario with the most variability, Eq. 2 was used to find the minimum number of repetitions (56) to guarantee that the error in the outcome results are within 5% of the maximum error with 95% of confidence. In total, 60 repetitions of each variation were run and the results represent the average of these runs.

$$n \geq \left[100 \cdot Z \cdot s / r \cdot \bar{x}\right]^2 = 56.61599 \rightarrow 60 \ \text{ samples} \tag{2}$$

Whereby,
Z = *confidence interval of 95%*; s = *standard deviation, 53.4287*
r = *maximum error of 5%*; $\bar{x}$ = *evacuation time average of 100 samples*

Simulation Results Comparing the Models. This experiment was conducted according to Table 2 comparing the influence of each factor of the initial model [15] with the current IMPACT model. Figure 2 compares the average evacuation time of the two models, varying familiarity and social contagion as described in Table 2. For all cases the current IMPACT model presented higher evacuation times than the old model. Even comparing social contagion of the models with themselves, it is clear that the influence of social contagion on the current IMPACT model, was not visible in the old one. In relation to the number of falls, there was a drastically reduction for reasonable values. For example, in a simulation with 800 people the initial model has 368 falls on average, while the current IMPACT model has 16. For both, when the social contagion is activated it results in the duplication of falls, and no significant variability was observed in the average response time to evacuate after the incident started.

Table 2. Factors and levels in simulation experiment social contagion and familiarity.

Level	Factor				
	Crowd density	Familiarity	Social contagion	Environment type	Model
1	Low: 2 people/m^2	0%	On	Square room, 2 doors	Initial model [15]
2	Medium: 4 people/m^2	50%	Off		Current model
3	High: 8 people/m^2	100%			

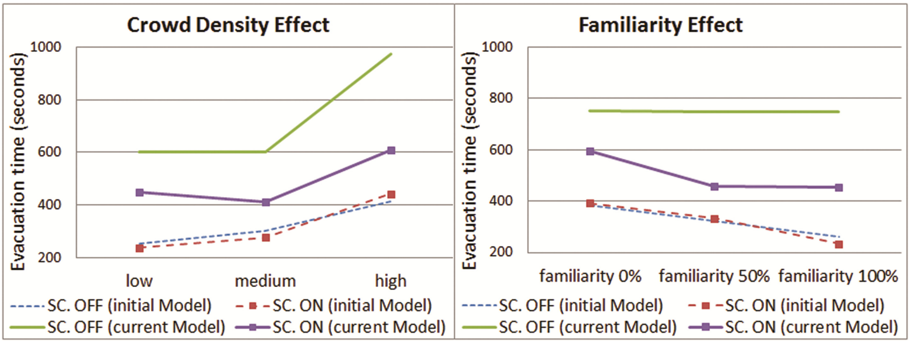

Fig. 2. Average evacuation time of the initial and current IMPACT models.

Simulation Results Exodus Benchmark. The project Exodus [6] was selected as benchmark of the model. It is a traditional model accepted by the specialists in this area [9]. The environment selected is called SGVDS1. It is a ship: a complex environment composed of 3 floors divided into sectors, with many escape route possibilities to the 4 exit areas. Figure 3 shows the floor plan of the ship which was imported to the simulator. An experiment was conducted comparing three versions of the current IMPACT model with the benchmark as the baseline model, see Table 3. The current IMPACT model covers more aspects than those required by the benchmark protocol. In order to make a fair validation some of the current IMPACT model's variables were fixed:

- Familiarity: It was assumed that everybody was not familiar with the environment.
- Relationship: It was assumed that no one has relationships with other passengers.
- Social contagion: Considered depending on experimental condition, see Table 3.
- The passenger`s speed in experiment 1 follow the patterns indicated in [5]. In experiment conditions 2 and 3, the speed was calculated by the current IMPACT model.
- Groups and help: Not considered in any experimental condition.

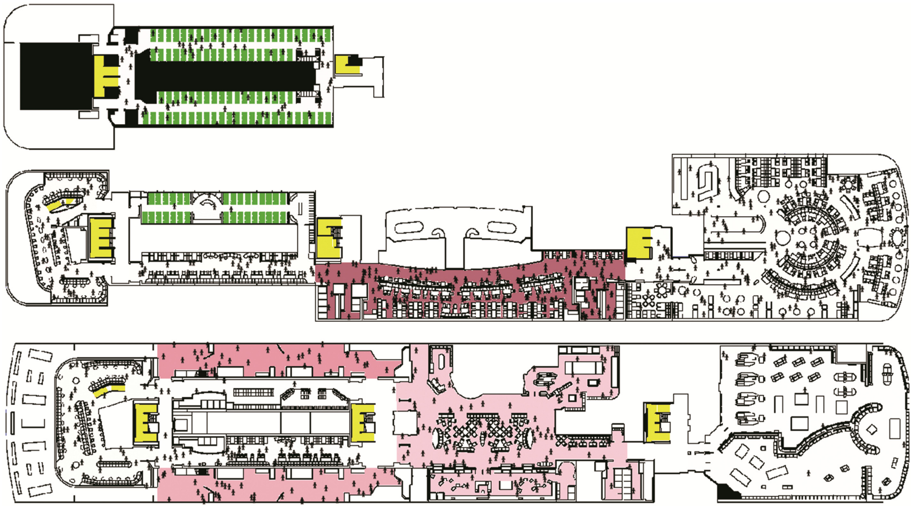

Fig. 3. Scenario of the software simulation.

The validation considers The Final Evacuation Time in Seconds (FET); the percentage difference between the predicted and Total Assembly Time (TAT); and the curve differences between the predicted and expected arrivals to the assembly areas (exits). This last measurement is calculated based on Euclidean Relative Difference (ERD), Euclidean Projection Coefficient (EPC) and Secant Cosine (SC).

Table 3. Results over validation protocol for the overall arrival times.

Condition:	Benchmark	Experimental Condition 1	Experimental Condition 2	Experimental Condition 3
Explanation:	Exodus SGVDS 1	No social contagion, response time and speed taken from the benchmark	No social contagion, response times and speed calculated by the model	Social contagion ON, response times and Speed calculated by the model
FET:	585	498.6	543.4	516.6
TAT:	0	14.77	7.11	11. 69
ERD:	0	0.568171	0.575657	0.565754
EPC:	0	0.724621	0.731295	0.731634
SC:	0	0.522105	0.423135	0.451471

In [5] it is stated that a 'good' TAT, should be below 40%. For all conditions this is true, indicating that the TAT in the experimental conditions are all 'good' and below 40%. For ERD, all experimental conditions are over, but close to, the expected boundary that is ≤ 0.45, while for EPC, the results do stay within the expected boundaries of $0.6 \leq \text{EPC} \leq 1.4$. For SC the values are below the expected boundary ≥ 0.6, and again close to the acceptance threshold. Figure 4 shows the curves for the 3 experiments compared to the experimental data.

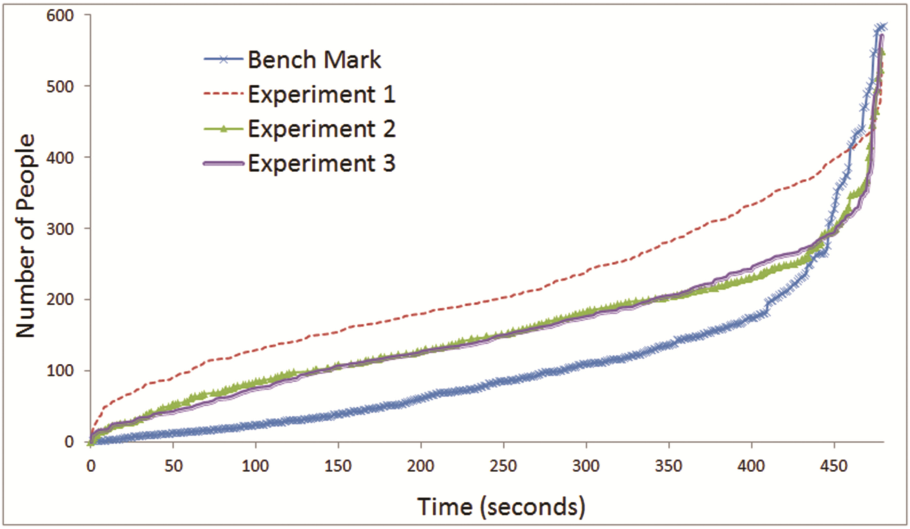

Fig. 4. Total arrival time pattern for one simulation run.

Simulation Results - Effect of Helping and Groups. In these structured simulations, the effects of helping and group formations on evacuation time, response time and number of falls are analysed. The hypotheses for the simulation experiments are: (1) evacuation time slows down when people are helping, because the helpers will need more time to evacuate; (2) groups have a higher effect in slowing down the evacuation time. Table 4 shows the experimental design.

Table 4. Factors and levels in simulation experiment helping and groups.

Level	Factor		
	Crowd density	Helping	Travelling alone
1	Low: 2 people/m^2	0%	100%
2	Medium: 4 people/m^2	50%	0% (only groups of 2 adults)
3	High: 8 people/m^2	100%	0% (only groups of 3 adults)
4			0% (only groups of 4 adults)

The factor helping has a considerable influence only for low crowd density, resulting, in average, 14% increase of total evacuation time (50 s more time to evacuate) with helping 'On'. While, for medium and high crowd densities this difference disappears. Figure 5 (left) shows the influence of helping on evacuation time. The discrepancy in results in low density environments can be explained by the few bottle-necks that are created in front of the exits. As many people stop their evacuation to help others as much is their contribution to delaying the evacuation. On the other hand, for medium and high crowd density scenarios, many people that are stuck in front of the exits are awaiting their chance of accessing the exits. In these cases, if some people stop their trajectory to help someone else, that time has few or almost no influence on the final evacuation time, since that same person will be stopped by other people close to the exit doors. The average response time (time to decide to evacuate and perform the actual evacuation for of each agent) does not present remarkable results in any of the scenarios.

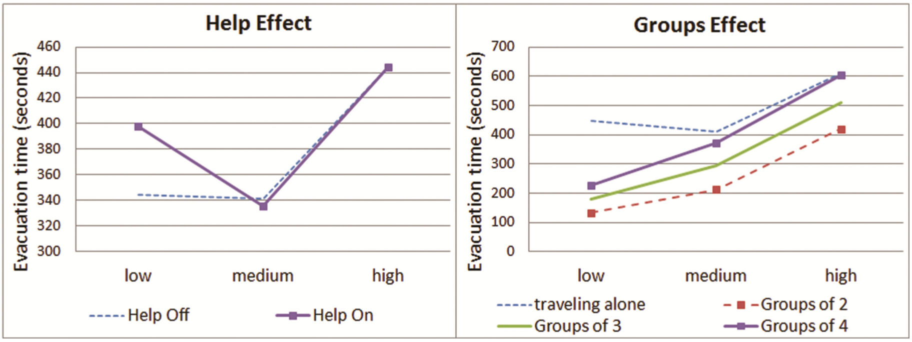

Fig. 5. Help and group factors influence over evacuation time to different crowd densities.

Contrary to expectations, the result in Fig. 5 (right) shows that groups reduced the average evacuation time. Groups of two presented the best results and the time increases when more people are added to a group. The explanation is social contagion. In groups the contagion of beliefs and emotions are spread faster than when all passengers travel alone. Therefore, groups evacuate faster than people travelling alone.

5 Discussion

This work aims to fill the gap in the research field of evacuation simulations by modelling evacuations including social and psychological factors in the model. This work is an extension of the initial proposed model in [15] and the new features were analysed and the model was validated. Existing features were refined and helping and group formation were added, approximating the model to reality in terms of evacuation time, falls and social interaction in crowded environments. Experiments were conducted to compare the outputs of both models. The current IMPACT model demonstrates clear improvements over the initial model in terms of evacuation time, falls and social influences in the agent's behaviour. Although the experiments presented in this work show the influence of social aspects individually, more experiments have to be conducted to analyse effects of combination of them. The cross relations between social effects and more complex environments might be explored, e.g. environments with pillars or multiple rooms.

A validation was conducted over a complex benchmark environment. The results are as expected and close to reality. All IMPACT model variations performed less than 7.11% to 14.77% (between 42 and 86 s) of difference from the benchmark's total evacuation time, which is a good TAT according to [13], and the curves of acceptance in Table 3 show values close to the prescribed boundaries, establishing the model's validity. For the future, it is recommended to apply new benchmarks over the model, increasing the confidence about the model's results.

To finalise, experiments that analysed the influence of helping and groups demonstrated interesting patterns useful for future security protocols. Social contagion effect creates faster evacuation time as expected, because information about the need for evacuation spreads faster than without social contagion. Furthermore, the more people are familiar with the environment: (1) the faster evacuation time and (2) the less falls. These results are a combination of a phased evacuation (less congestion) with more people spread through the environment going to the nearest exits, what leads to less falls as well, and social contagion (the decision to evacuate can spread faster), resulting in faster response and evacuation time. In case of helping, evacuation time increases only for low crowd density environments. For high crowd density environments the Helping effect is minimised for other effects that grow in importance like blocking of paths due to a number of people. Groups of two people reduce the evacuation time and as more people are added to a group this effect is reduced until it disappears. To conclude, the model has advantages over others that don't consider social effects in collective behaviour to evacuation scenarios, presenting reasonable results and can be used to predict real scenarios. As next steps, new social aspects will be incorporated and more benchmarks will be applied to it.

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