# Simulating Crowd Evacuation with Socio-Cultural, Cognitive, and Emotional Elements

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**Abstract.** In this research, the effects of culture, cognitions, and emotions on crisis management and prevention are analysed. An agent-based crowd evacuation simulation model was created, named IMPACT, to study the evacuation process from a transport hub. To extend previous research, various socio-cultural, cognitive, and emotional factors were modelled, including: language, gender, familiarity with the environment, emotional contagion, prosocial behaviour, falls, group decision making, and compliance. The IMPACT model was validated against data from an evacuation drill using the existing EXODUS evacuation model. Results show that on all measures, the IMPACT model is within or close to the prescribed boundaries, thereby establishing its validity. Structured simulations with the validated model revealed important findings, including: the effect of doors as bottlenecks, social contagion speeding up evacuation time, falling behaviour not affecting evacuation time significantly, and travelling in groups being more beneficial for evacuation time than travelling alone. This research has important practical applications for crowd management professionals, including transport hub operators, first responders, and risk assessors.

**Keywords:** Crowd behaviour · Crowd management · Crowd simulation · Evacuation · Emotional contagion · Social dynamics · Culture · Cognition · Group-decision making

## 1 Introduction

Crisis management and prevention involves preparing for many different emergency situations. This research focuses on studying the socio-cultural, cognitive, and emotional factors influencing an evacuation from a building, such as a transport hub. This is important, because few crisis managers and risk assessment professionals currently deal with these factors and their resulting behaviours. Accordingly, this research developed and validated a crowd evacuation simulation model that includes socio-cultural, cognitive, and emotional factors in order to simulate what-if scenarios. Consequently, it

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will help transport hub operators, crisis managers, risk assessment professionals, and policy makers understand human behaviour, deal with socio-cultural crowd diversity, and ultimately save lives.

Faster evacuation from public buildings during emergencies saves more lives. Observations of actual emergencies show that people tend to be slow to respond to evacuation alarms (taking up to 10 min) and take the familiar route out instead of the nearest exit [4, 7, 14, 21, 23, 30]. These risky behaviours stem from being unfamiliar with the environment, not seeing immediate signs of danger, and following others' (unsafe) behaviour, leading to preventable deaths in many disasters. For instance, in the Station Nightclub fire, in Rhode Island in 2003, the majority of people tried to escape back through the familiar main entrance, leading to falls, crushing, and 100 deaths. Many of the 56 deaths in the Bradford City Stadium fire in 1985 could have been prevented if response time to the fire had been faster [3], and similarly slow responses were found among occupants of the World Trade Center towers during the 9/11 terror attacks in New York City [23]. In recent emergencies, some people have even remained in dangerous areas to film events with their smartphones instead of escaping (Nice Boulevard, 14/07/2016; Westgate Shopping Centre, Nairobi, 21/9/2013).

Current crowd evacuation models simulate how crowds move through built environments [9], enabling ethical tests of how to improve crowd movements in emergency evacuations. In addition to informing how to build safer buildings, computer models can identify safer behaviours in existing buildings. For example, it is well-documented that not running leads to faster evacuations due to fewer falls and less congestion at the exit [17, 36]. However, traditional computer models of evacuations have been criticized for being unrealistic, because they treat people as 'moving particles' with identical characteristics [9, 36]. Such models wrongly assume that all people will respond to alarms without delay, know their way, and take the nearest exit. As noted above, however, each of these assumptions has been proven wrong [4, 7, 14, 21, 23, 30].

The aim of this research, therefore, is to develop and validate an evacuation simulation model that includes socio-cultural, cognitive, and emotional factors, to address the need for crowd models to incorporate more realistic human behaviours. To do so, the model developed here draws on insights from social and cross-cultural psychology, interviews with crisis management experts, and is based on scientific findings and literature. Furthermore, the model is validated against data from an evacuation drill related to the existing EXODUS evacuation model [13, 26]. It is intended that this model will help transport hub operators, crisis managers, risk assessment professionals, and policy makers understand human behaviour, deal with socio-cultural crowd diversity, and ultimately save lives.

The paper is organised as follows. First, the background literature on crowd evacuation models is reviewed and the current approach is introduced in Sect. 1.1. In Sect. 2, the formal model is presented, followed by the validation and simulation results in Sect. 3. The work is then summarised and discussed in Sect. 4.

### 1.1 Background Evacuation Models

There are many different approaches for crowd evacuation simulations, of which Zheng et al. [48] describe seven: (1) cellular automata, (2) lattice gas, (3) social force, (4) fluid dynamics, (5) agent-based, (6) game theory, and (7) animal experiments. In microscopic models (e.g. cellular automata, lattice gas, social force, agent-based models), the pedestrian is modelled as a particle. However, in macroscopic models (e.g. fluid dynamic models), a crowd of pedestrians is modelled as a fluid. In conclusion, Zheng et al. [48] concluded that in further research, evacuation models should: (1) combine different approaches, and (2) incorporate psychological and physiological elements. Our IMPACT model addresses both of these recommendations.

Moreover, Templeton et al. [39] conclude that current crowd simulations do not include psychological factors and therefore cannot accurately simulate the collective behaviour that has been found in extensive empirical research on crowd events. Specifically, they argue that crowd members should be able to identify with other people in crowd simulations to form psychological sub-groups known as in-groups. This is critical for evacuation models, as research indicates that people are more likely to help fellow in-group members during emergencies [8]. Accordingly, our IMPACT model also incorporates social identity.

Most of the evacuation models that Santos and Aguirre [36] reviewed do not model social dimensions, such as group decision making, but focus more on physical constraints and factors such as walking speed, walkways, and stairways, to find the optimal crowd flow for the evacuation process. Agents are rational in these simulations: they can find the optimal escape route, avoid physical obstructions and, in some models, even overtake another person obstructing them. However, even though these models do include parameters like gender, age, individual walking speeds, and different body dimensions, they still lack socially interactive characteristics such as the monitoring of others. Again, to address this, our IMPACT model incorporates such social processes.

Santos and Aguirre [36] also reviewed the incorporation of social and psychological factors into evacuation simulation models, noting their inclusion in three models: (1) FIRESCAP, (2) EXODUS, and (3) Multi-Agent Simulation for Crisis Management (MASCM). EXODUS includes 22 social psychological attributes and characteristics for each agent, including age, sex, running speed, dead/alive, and familiarity with the building. Agents can also perform tasks before evacuating the building, such as picking up a purse or searching for a lost child. Still, the agents in EXODUS cannot have micro-level social interactions that would create a collective understanding of the situation for the group. However, MASCM does include social interaction with so-called 'evacuation leaders' who can communicate ('please follow me') and start to walk along the evacuation route, or find an evacuee, or wait for an evacuee to approach them. Finally, FIRESCAP implements the social theory of 'collective flight from a perceived threat'. The egress is a result of a socially-structured decision making process guided by norms, roles, and role relations.

From this literature review, it can be concluded that the ideal simulation approach for realistic crowd evacuation models should seek to develop sub-models that include an active, 'investigative', socially-embedded agent that assesses the state of other people and defines the situation collaboratively. Essentially, then, group dynamics must be considered, and our IMPACT model aims to address this.

## 1.2 Current Approach

Based on the lack of psychological and socio-cultural factors in existing evacuation models, we created our IMPACT evacuation model based on an earlier model called ASCRIBE [2]. This allows for the social contagion of emotional and mental states, and enables group decision making and other social dynamics [1, 2]. The ASCRIBE model has outperformed other models in reproducing real crowd panic scenes and was extended here with many psychological and socio-cultural factors – such as familiarity, falls, and prosocial behaviour – and applied to a specific evacuation scenario [41]. The evacuation dynamics were modelled using agent-based belief-desire-intention (BDI) and network-oriented modelling approaches [32, 40]. A first version of the IMPACT model was introduced in [43] and the further-developed and validated model was introduced in [12]. The final version of the IMPACT model presented here has now been fully refined and certain characteristics have been updated. We introduce it here with its most important findings. The updates concern speed, falls, compliance levels, egress flowrate, observation distance, helping behaviour, and cultural divisions, and these are based on psychological and socio-cultural research as described below.

## 1.3 Background Psychological and Socio-Cultural Factors in the IMPACT Model

**Overview.** Although the computer simulation of crowd behaviour has been ongoing for several decades, most existing models are still founded on erroneous assumptions of human behaviour and movement as linear, logical, and driven primarily by the laws of physics [4]. A key reason for this has been the disciplinary division in crowd behaviour research. Modellers engaged in crowd simulation are typically drawn from technical fields, such as computer science and engineering, while psychologists and other social scientists who study crowd behaviour do not generally use computer simulation methods [18]. Consequently, only truly interdisciplinary research can effectively simulate crowd behaviour, particularly in emergencies, in complex systems comprising both social and technical elements [5]. To address these issues in our IMPACT model, alongside the conventional features of traditional crowd simulation models we have included additional psychological and socio-cultural elements. For instance, at an individual level, we have simulated the effect of people's socio-cultural characteristics such as age, gender, and nationality on their behaviour (e.g. based on the national cultural clusters in [35]) in emergencies; while, at a group level, we have simulated social processes such as social identity [8] and emotional contagion [1, 2].

**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. [46], 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 [38], where 8 is the maximum number of people per square metre and 4 the number of people at 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 as the agent and if he is running faster than 3 m/s, then there is a 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 [33] study of gender differences in hurricane evacuation, modified for different age groups using data from Soto et al.'s [37] 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.

**Egress flowrate at each exit.** The maximum flowrate is 6 people per exit per second (p/m/s), based on guidelines from Still [38] indicating an egress flowrate of 82 people/metre/minute (p/m/m), equivalent to 1.37 p/m/s, then multiplied by 4 (as doors are 4 m wide) to indicate 5.47 people per exit door per second.

**Observation distance.** Public distance (space in which social interactions are still possible, extending the personal and formal social interaction space) is 12–25 feet (3.7–7.6 m), in relation to public speaking to large groups, while no social interaction is possible over 25 feet [15], though this might not take shouting into account. Considering the size of the environment that was implemented in the model (e.g. a square room of $20 \times 20$ m), it was decided to keep the observation distance (i.e. the maximum distance at which staff instructions could be understood) at 5 m rather than 10. Otherwise, at 10 m, the passengers could observe everything in the building from the centre and the important effects of social contagion would be downplayed in the simulations.

**Helping.** The probabilities of helping others during the emergency evacuation were modelled as a function of the characteristics of helpers and fallers. This was based on research indicating that, in emergencies: (a) men are most likely to help others, (b) women, children, and older adults are most likely to receive help [10], and (c) people are more likely to help members with a shared identity [8]. The precise probabilities can be found in Sect. 2.1.

**Culture.** In the model, the passengers are divided into different clusters of culturally similar nationalities based on previous research [35]. Data concerning the percentage of English speakers for each country in each cluster were then obtained, where available, from multiple verified and official sources compiled by Wikipedia [45]. We then calculated a weighted average percentage of English speakers in each cluster – using the population sizes of each cluster's constituent countries – and these were the values used in the simulation model to determine the percentage of passengers from each cluster who could understand an English instruction by a staff member or public announcement. The precise probabilities can be found in Sect. 2.1.

**Group decision making.** Like in previous work [1, 2], group decision making is based on findings from social neuroscience to make a biologically plausible human-like model. Decision making is modelled as both an individual process called somatic marking and a social group process based on mirroring of cognitive and emotional states [6, 34]. Damasio's somatic marking hypothesis is a theory of decision making which provides a central role to emotions felt [6]. Each decision option induces a feeling to mark that option. In social neuroscience, neural mechanisms have been discovered that account for mutual mirroring effects between mental states of different people. For example, when one expresses an emotion in a smile, another person can observe this smile which automatically triggers preparation neurons (called mirror neurons) for smiling within this other person and consequently generates the same emotion. Similarly, mirroring of intentions and beliefs can be considered. This is called emotional contagion (for emotions alone) or social contagion (for emotional and mental states) in this work.

## 2 Model

### 2.1 Formal Model

Figure 1 gives an overview of the formal model, showing the four modules of each passenger and how they interact. The passenger has individual characteristics – such as age, gender, familiarity, and group membership – which influence their interactions. For example, familiarity influences the choice of exit (people-environment interaction), while age, gender, and group membership influence the pro-social behaviour (people-people interactions). The full details of these four modules, their constituent

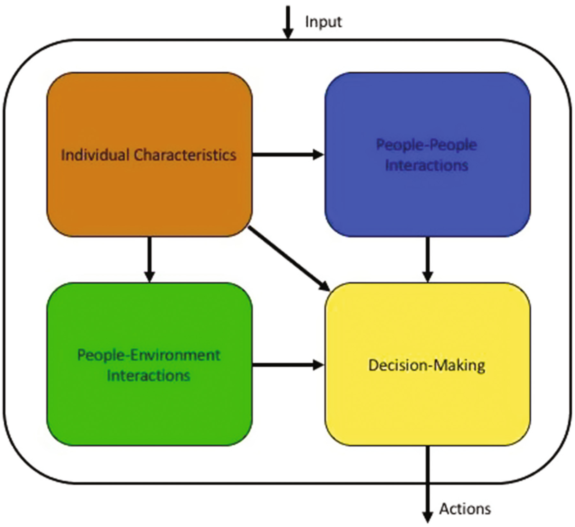


**Fig. 1.** Agent modules in the IMPACT evacuation model

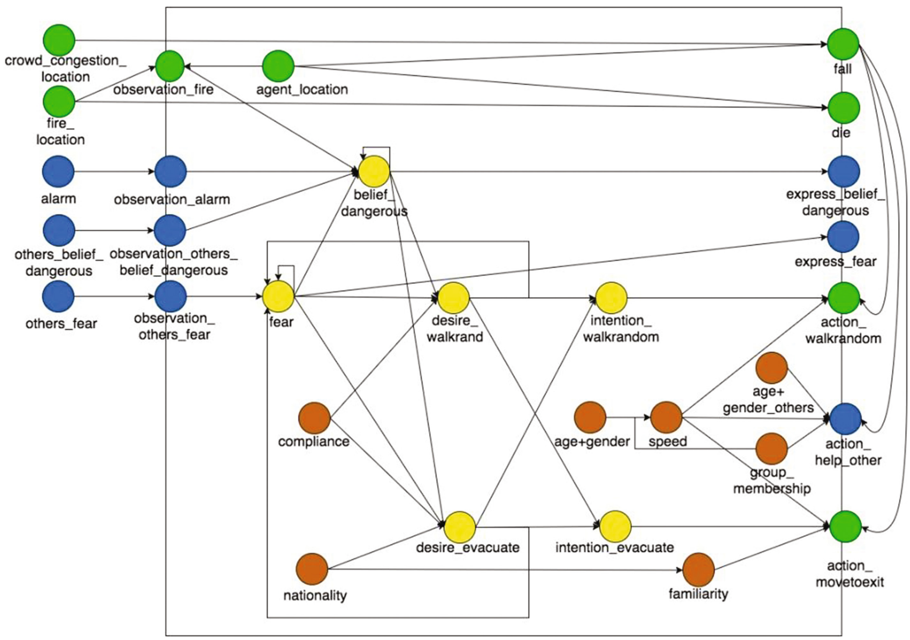


**Fig. 2.** Dynamic relationships between concepts in the IMPACT evacuation model

concepts, and their dynamic relationships are shown in Fig. 2, using the same coloured key as Fig. 1 for the modules.

Below, all the formal rules of the proposed model are presented in the form of mathematical formulas representing all dynamic relationships between all concepts from Fig. 2. Creating the formal model in this way, using mainly difference equations, is based on the network oriented modelling approach [40].

Firstly, the following environmental states have the value 0 (‘off’) or 1 (‘on’). These are ‘inputs’ of the model and vary over time. For example, the fire_alarm is ‘on’ after three minutes of the simulation and the public_announcement is ‘on’ one minute after the fire_alarm is ‘on’.

$$\text{crowd\_congestion\_location(t); fire\_location(t); alarm(t); staff\_instructions(t);} \\ \text{public\_announcement(t)} \tag{1}$$

The aggregated impacts of others on agent $x$, for the levels of the belief that the situation is dangerous and the levels of fear, are calculated as a weighted sum at every time step, based on previous work [1, 2]:

$$\begin{aligned} &\text{others\_belief\_dangerous}_x(\text{t}) = ssum_\lambda(\omega_{y1x} \cdot belief\_dangerous_{y1}, \ldots, \omega_{kx} \cdot \\ &belief\_dangerous_k) = ssum_\lambda(\omega_{y1x} \cdot belief\_dangerous_{y1} + \ldots + \omega_{kx} \cdot \\ &belief\_dangerous_k) = \frac{\sum_k^{y1} \omega_{y1x} \cdot belief\_dangerous_{y1}(t)}{\sum_k^{y1} \omega_{y1x}}. \end{aligned} \tag{2}$$

$$\text{others\_fear}_x(\mathrm{t}) = ssum_\lambda\left(\omega_{y1x}\cdot fear_{y1},\ldots,\omega_{kx}\cdot fear_k\right) = ssum_\lambda(\omega_{y1x}\cdot fear_{y1}+\ldots+\omega_{kx}\cdot fear_k\big) = \frac{\sum_k^{y1}\omega_{y1x}\cdot fear_{y1}(t)}{\sum_k^{y1}\omega_{y1x}}. \tag{3}$$

whereby $\lambda = \sum_k^{y1}\omega_{y1x}$

All observations of events or other passengers are calculated as stated below. The observation_fire becomes 1 if the passenger is within a distance of 5 m, representing the observation distance which is adjustable by the modeller, based on [15], see Sect. 1.3. When the fire alarm sounds, then 50% of the time the passenger will observe this alarm and this, in turn, will change the passenger's belief_dangerous to 1. This represents the risk-taking passengers have, as not all passengers react quickly to a fire alarm [21, 23, 30]. Note that, for example, for observation_others_fear(t) = others_fear(t) a simplification of the real world has been made to model the values to match each other instantaneously instead of with a delay, as further detail was not necessary in the model.

$$\text{observation\_fire(t) = 1 if }\left(\sqrt{(x_1-x_2)^2+(y_1-y_2)^2}\leq 5\right)\text{ else 0; where by agent\_location(t) = }(\mathrm{x}_1\ \mathrm{y}_2)\text{ and fire\_location(t) = }(\mathrm{x}_2\ \mathrm{y}_2). \tag{4}$$

$$\mathrm{P(observation\_alarm(t)} = 1\,|\,\mathrm{alarm(t)} = 1) = 0.5. \tag{5}$$

$$\begin{aligned}\text{observation\_others\_belief\_dangerous(t)} &= \text{others\_belief\_dangerous(t)};\\ \text{observation\_others\_fear(t)} &= \text{others\_fear(t)};\\ \text{observation\_staff\_instr(t)} &= \text{staff\_instructions(t)};\\ \text{observation\_pa(t)} &= \text{public\_announcement(t)}\end{aligned} \tag{6}$$

If there is a fire at the same location as the passenger, then the passenger dies. Die(t) has a binary value of 0 ('not dead') or 1 ('dead'). This strict rule was chosen as more detail was not necessary for the goal of this model. We chose not to model the effect of the fire and smoke, like the heat and toxicity in the room, so we could purely focus on the human behavioural effects in the simulations not combined with the effects of the fire.

$$\text{die(t)} = 1(\text{if fire\_location} == \text{agent\_location})\text{ else }0\,. \tag{7}$$

Each passenger has an initial speed based on his/her age and gender, based on [38, 46], see Sect. 1.3.

At t = 0:

- If age + gender = female adult then basic speed = 0.9 + rand (0, 0.5).
- If age + gender = male adult then basic speed = 1 + rand (0, 0.5).
- If age + gender = child then basic speed = 0.5 + rand (0, 0.5).
- If age + gender = female elderly then basic speed = 0.9 + rand (0, 0.5).
- If age + gender = male elderly then basic speed = 0.9 + rand (0, 0.5).
- If group_membership = 1, then speed = min(basic speeds of other members)

$+ 0.4 \cdot (\max(\text{basic speeds of other members}) - \min(\text{basic speeds of other members}).$

- If group membership $=$ 0, then speed $=$ basic speed. (8)

Whereby: rand is a random number, min = minimum, and max = maximum.

Each passenger has an initial compliance level based on his/her age and gender, based on [33, 37], see Sect. 1.3.

At t = 0:

- If age + gender = male child then compliance = 0.89.
- If age + gender = female child then compliance = 0.89.
- If age + gender = male adult then compliance = 0.89.
- If age + gender = female adult then compliance = 0.94.
- If age + gender = male elderly then compliance = 0.92.
- If age + gender = female elderly then compliance = 0.97.

(9)

Each passenger has a 5% chance (i.e., a 0.05 probability) of falling when there is crowd congestion at their location, as explained in Sect. 1.3. Fall(t) has a binary value of 0 (‘not fallen’) or 1 (‘fallen’).

$$\mathrm{P(fall(t)} = 1|\mathrm{crowd\_congestion\_location} == \mathrm{agent\_location)} = 0.05. \tag{10}$$

Each passenger has a belief about how dangerous the situation is. This belief has a value between 0 (‘minimum danger’) and 1 (‘maximum danger’). The belief will increase to 1 when a fire or alarm is sensed. The beliefs of other passengers can decrease or increase the passenger’s own belief, based on mirroring/contagion mechanisms as described in Sect. 1.3, based on previous research [1, 2]. The passenger’s fear level influences his belief (somatic marking): if the amount of fear is higher than the belief, it will increase the belief, and if the amount of fear is lower than the belief, it will decrease the belief. The belief is also based on the passenger’s belief from the previous time-step (persistence). The equations are presented in both difference and differential equation format to show how, hereafter, every difference equation can be translated into a differential equation.

$$\begin{aligned}&\mathrm{belief\_dangerous(t+\Delta t)} = \mathrm{belief\_dangerous(t)} + \eta \cdot (\max(\omega_{sensing} \cdot fire(t), \omega_{sensing} \cdot \\ &alarm(t), \omega_{persisting} \cdot belief\_dangerous(t), sum\left(\frac{\omega_{affectivebiasing} \cdot fear(t) + aggbeliefs_x(t)}{\omega_{affectivebiasing} + 1}\right)) - \\ &belief\_dangerous(t)) \cdot \Delta t.\end{aligned} \tag{11}$$

$$\begin{aligned}&\frac{dbelief\_\mathrm{dangerous}}{d\mathrm{t}} = \eta \cdot (\max(\omega_{sensing} \cdot fire(t), \omega_{sensing} \cdot alarm(t), \omega_{persisting} \cdot \\ &belief\_dangerous(t), sum\left(\frac{\omega_{affectivebiasing} \cdot fear(t) + aggbeliefs_x(t)}{\omega_{affectivebiasing} + 1}\right) - belief\_dangerous(t))\cdot\end{aligned} \tag{12}$$

whereby, $\text{aggbeliefs}_x(\text{t}) = ssum_\lambda(\omega_{y1x} \cdot belief\_dangerous_{y1}(t), \ldots, \omega_{kx} \cdot belief\_dangerous_k(t)) = ssum_\lambda(\omega_{y1x} \cdot belief\_dangerous_{y1}(t) + \ldots + \omega_{kx} \cdot belief\_dangerous_k(t)) = \frac{\sum_k^{y1} \omega_{y1x} \cdot belief\_dangerous_{y1}(t)}{\sum_k^{y1} \omega_{y1x}}$.
$\lambda = \sum_k^{y1} \omega_{y1x}$

The amount of fear a passenger feels is based on the fear level of the previous time-step (persistence), the levels of intentions to evacuate (amplifying fear) or walk randomly (decreasing fear), the other passengers' levels of fear (emotional contagion), and the staff instructions or public announcements they observe (decreasing fear). These processes are based on mirroring/contagion mechanisms as described in Sect. 1.3, based on previous research [1, 2]. The fear value ranges from a minimum of 0 ('no fear') to a maximum of 1 ('maximum fear').

$$\text{fear}(\text{t} + \Delta\text{t}) = \text{fear}(\text{t}) + \eta \cdot (\max\,(\omega_{persisting} \cdot fear(t), alogistic(aggfears(t), \omega_{amplifyingfeeling} \cdot desire_{evacuate(t)}, \omega_{inhibitingfeeling} \cdot desire_{walkrand(t)}, \omega_{decreasingfear} \cdot observation_{staf_{instr(t)}}, \omega_{decreasingfear} \cdot observation_{pa(t)})) - fear(t)) \cdot \Delta t. \tag{13}$$

whereby, aggfears(t) is calculated similarly as $\text{aggbeliefs}_\text{x}(\text{t})$ (see Eq. 12) and $alogistic_{\sigma\tau}(V_1, \ldots, V_k) = (\frac{1}{1 + e^{-\sigma(V_1 + \ldots + V_k - \tau)}}) - \frac{1}{1 + e^{\sigma\tau}})(1 + e^{-\sigma\tau})$.

The desire to evacuate value ranges from 0 ('minimal desire') to 1 ('maximal desire'). It is amplified by the level of compliance, the passenger's belief of how dangerous the situation is (cognitive responding), the passenger's level of fear (somatic marking), and staff instructions or public announcements to evacuate. The somatic marking and cognitive responding are processes based on mirroring/contagion mechanisms as described in Sect. 1.3, based on previous research [1, 2].

$$\text{desire\_evacuate}(\text{t} + \Delta\text{t}) = \text{desire\_evacuate}(\text{t}) + \eta \cdot ((compliance \cdot (\max(\omega_{amplifyingevacuation} \cdot belief\_dangerous(t), \omega_{amplifyingevacuation} \cdot fear(t), \omega_{amplifyingevacuation} \cdot observation\_staff\_instr(t), \omega_{amplifyingevacuation} \cdot observation\_pa(t)))) - desire\_evacuate(t)) \cdot \Delta t. \tag{14}$$

Whereby,
$ssum_\lambda(\omega_1 \cdot V_1(t), \ldots, \omega_k \cdot V_k,) = ssum_\lambda(\omega_1 \cdot V_1(t), \ldots, \omega_k \cdot V_k,) = \frac{\sum_k^1 \omega_1 \cdot V_1(t)}{\sum_k^1 \omega_1}$, $\lambda = \sum_k^1 \omega_1$.

The value of the desire to walk randomly ranges from 0 ('minimal desire') to 1 ('maximal desire'). It is inhibited by the level of compliance, the passenger's belief of how dangerous the situation is (cognitive responding), the passenger's level of fear (somatic marking), and staff instructions or public announcements to evacuate. The somatic marking and cognitive responding are processes based on mirroring/contagion mechanisms as described in Sect. 1.3, based on previous research [1, 2].

$$\mathrm{desire\_walkrand}(\mathrm{t}+\Delta\mathrm{t}) = \mathrm{desire\_walkrand}(\mathrm{t}) + \eta \cdot (compliance \cdot (1 - \max(\omega_{inhibitingwalkrand} \cdot belief\_dangerous(t), \omega_{inhibitingwalkrand} \cdot fear(t), \omega_{inhibitingwalkrand} \cdot observation\_staff\_instr(t), \omega_{inhibitingwalkrand} \cdot observation\_pa(t)) - desire\_walkrand(t)) \cdot \Delta t. \tag{15}$$

The intention to evacuate value ranges from 0 (‘minimal intention’) to 1 (‘maximal intention’), and so too does the intention to walk randomly value. To decide whether the desire to evacuate or walk randomly is larger, a logistic function is used, and this outcome is then multiplied by the desire to walk randomly. This, in turn, is multiplied by (1-fall(t)) to make sure it is only a value larger than 0 when the passenger has not fallen. When the passenger has fallen, the value will become 0, then the passenger cannot actually walk randomly or evacuate.

$$intention\_evacuate(t+\Delta\mathrm{t}) = intention\_evacuate(t) + \eta \cdot ((1 - \mathrm{fall}(t)) \cdot desire\_evacuate(t) \cdot \mathrm{logistic}((\omega_{amplifyingintention} \cdot desire\_evacuate(t), \omega_{inhibitingintention} \cdot desire\_walkrand(t)) \cdot \Delta t. \tag{16}$$

$$intention\_walkrand(t+\Delta\mathrm{t}) = intention\_walkrand(t) + \eta \cdot ((1 - \mathrm{fall(t)}) \cdot desire\_evacuate\,(t) \cdot \mathrm{logistic}((\omega_{inhibitingintention} \cdot desire\_evacuate\,(t), \omega_{amplifyingintention} \cdot desire\_walkrand(t)) \cdot \Delta t. \tag{17}$$

whereby: $logistic_{\sigma,\tau}(V_1, \ldots, V_k) = \frac{1}{1+\mathrm{e}^{-\sigma(V_1+\ldots+V_k-\tau})})$.

The action movetoexit is a combination of the speed of the passenger and his target (i.e. the location/exit he moves towards). The value of the intention to evacuate influences the speed of moving to the exit. The familiarity, observation of staff instructions, and the public announcement all influence the choice of exit [4, 14].

$$\text{If (familiarity} = 1 \text{ OR observation\_staffinstructions} = 1 \text{ OR observation\_pa} = 1) \text{ then action\_movetoexit(t)} = (\text{target} = \text{nearest exit}) \text{ AND } (\text{speed} = \text{intention\_evacuate(t)} \cdot \text{speed}) \text{ else action\_movetoexit(t)} = (\text{target} = \text{entrance}) \text{ AND } (\text{speed} = \text{intention\_evacuate(t)} \cdot \text{speed}). \tag{18}$$

The action walkrandom is a combination of the speed and heading of the agent in the environment. The value of intention_walkrand is multiplied by the maximum speed of the agent.

$$\text{action\_walkrand(t)} = (\text{heading} = \text{random}) \text{ AND } (\text{intention\_walkrand} \cdot \text{speed}). \tag{19}$$

The action help_other is calculated as stated below, based on previous research [8, 10], as described in Sect. 1.3.

When

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \leq 5. \tag{20}$$

**Table 1.** Probabilities of helping a fallen passenger

| Helper passenger | Social identity | Fallen passenger | | | | | |
|---|---|---|---|---|---|---|---|
| | | Male child | Male adult | Male elderly | Female child | Female adult | Female elderly |
| Male adult | In-group | 0.30 | 0.15 | 0.30 | 0.40 | 0.30 | 0.40 |
| Male elderly | In-group | 0.15 | 0.08 | 0.15 | 0.20 | 0.15 | 0.20 |
| Male adult | Out-group | 0.25 | 0.13 | 0.25 | 0.34 | 0.25 | 0.34 |
| Male elderly | Out-group | 0.13 | 0.06 | 0.13 | 0.17 | 0.13 | 0.17 |
| Female adult | In-group | 0.15 | 0.08 | 0.15 | 0.20 | 0.15 | 0.20 |
| Female elderly | In-group | 0.08 | 0.04 | 0.08 | 0.10 | 0.08 | 0.10 |
| Female adult | Out-group | 0.13 | 0.06 | 0.13 | 0.17 | 0.13 | 0.17 |
| Female elderly | Out-group | 0.06 | 0.03 | 0.06 | 0.08 | 0.06 | 0.08 |

whereby agent_location(t) = ($x_1$ $y_2$) and agent_location of other passenger(t) = ($x_2$ $y_2$) and other passenger fall(t) = 1, then the chance of helping depends on the age + gender of the helper and the fallen passenger and whether they share a social identity (in-group) or not (out-group). The overall probability of helping is shown in Table 1.

The expressions of fear and the passenger's belief of the situation are modelled in a simple way, where the values match each other instantaneously instead of with a delay, as further detail was not necessary in the model.

$$\mathrm{express\_belief\_dangerous(t)} = \mathrm{belief\_dangerous(t)};\ \mathrm{express\_fear(t)} = \mathrm{fear(t)} \quad (21)$$

### 2.2 Pseudo-code and Model Overview

The model was implemented in the NetLogo multi-agent language [25]. To do so, the formal model presented in the previous section was transformed into multiple IF THEN rules. An example of how these rules were translated into NetLogo code is shown below, taking Formula *18* (see previous section) as an example. It is shown that for each agent in the model the heading (direction) is set as a random number between 0 and 360 (degrees), and then based on the age and gender of the agent a speed is also set. Then, for the action to walk randomly, the level of the intention is multiplied by the speed.

```
;-- EXAMPLE RULE IN NETLOGO --
ask agents [
    set heading random 360
    if st_gender = 0 and st_age = 1 [set speed 0.9 +
random-float 0.52]   ;female adult
    set st_action_walkrandom st_intention_walkrand *
speed
]
```

Figure 3 shows the activity diagram of the created simulator focusing on the internal model. The system updates internal states and actions of each agent. After that, it updates the environment, considering the actions of the agents, and finalizes the cycle by updating the statistics. The simulation stops when all agents are either evacuated or dead. At any moment, the user can change the parameters available on the interface and influence the environment or agents.

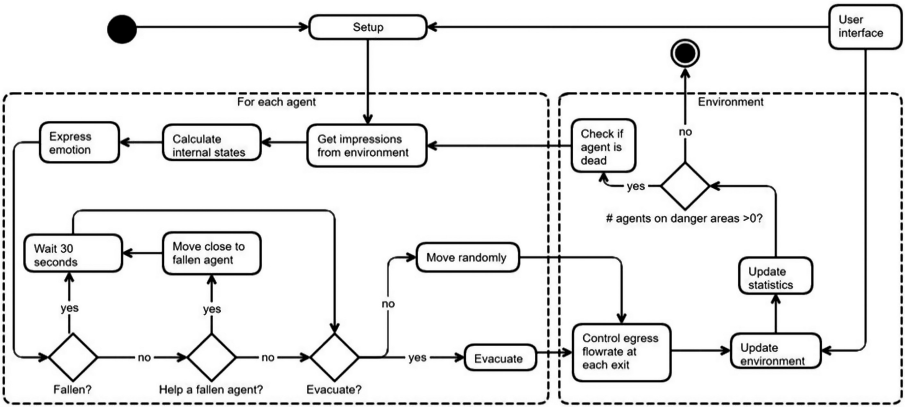


**Fig. 3.** Activity diagram overview of the IMPACT crowd evacuation model

# 3 Validation and Structured Simulation Results

## 3.1 Validation Results: IMPACT Model Versus EXODUS Benchmark

Our IMPACT model has been compared with a benchmark to establish its validity. In [12] the validation process and results have been explained and discussed already, and a summary is provided here. The EXODUS model [26] was selected as a benchmark

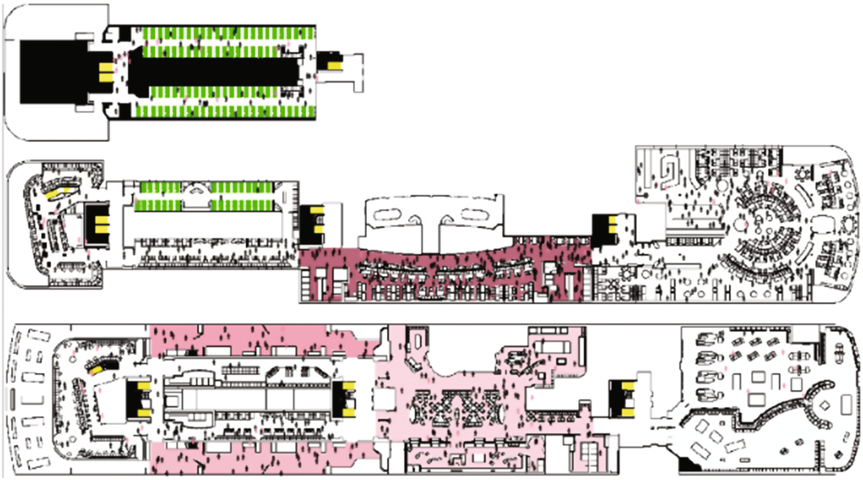

**Fig. 4.** Scenario of the software simulation.

for the IMPACT model, as it is accepted by specialists in this area as realistic [26]. The environment selected is called SGVDS1, a complex ship environment composed of three floors, with different escape routes to the four assembly areas [13] (Fig. 4).

A validation experiment was conducted comparing three versions of the IMPACT model with the benchmark of the EXODUS model (see Table 2 for the experimental design). The IMPACT model covers more aspects than the benchmark EXODUS model, however, so some of the IMPACT model's variables were fixed to enable a fair comparison:

**Table 2.** Results of the validation protocol for the overall arrival times.

| Condition | Benchmark | Experimental condition 1 | Experimental condition 2 | Experimental condition 3 |
|---|---|---|---|---|
| Explanation | Exodus SGVDS1 data | No Social Contagion. Response time and Speed taken from the benchmark | No Social Contagion. Response times and Speed calculated by the model itself | Social Contagion activated. Response times and Speed calculated by the model itself |
| FET | 585 (s) | 498.6 (s) | 543.4 (s) | 516.6 (s) |
| 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 |

- Familiarity: it was assumed that everybody was not familiar with the environment.
- Relationship: it was assumed that all passengers were unrelated.
- Social contagion: this was ‘on’ or ‘off’, depending on the experimental condition (see Table 2).
- The passenger’s speed: in experimental condition 1 the speeds indicated in [13] were used. In experimental conditions 2 and 3, the speed was calculated by the IMPACT model.
- Groups and Helping: these were not considered in any experimental condition.

The outcome measures of the validation experiment are: (1) Final Evacuation Time (FET); (2) the percentage difference between the predicted and Total Assembly Time (TAT); (3) 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). In [13] it is stated that a ‘good’ TAT should be below 40, which is true for all experimental conditions here. For ERD, all experimental conditions are over, but close to, the expected boundary that is $\leq$ 0.45, while for EPC, the results stay within the expected boundaries of 0.6 $\leq$ EPC $\leq$ 1.4. For SC, the values are below the boundary 0.6, but close to the acceptance threshold. See Table 2 for all the results. In Fig. 5 below, the assembly curves of the benchmark and the three IMPACT versions (the three experimental conditions) are shown. These results show that on all measures, the IMPACT model is within or close to the prescribed boundaries, thereby establishing its validity.

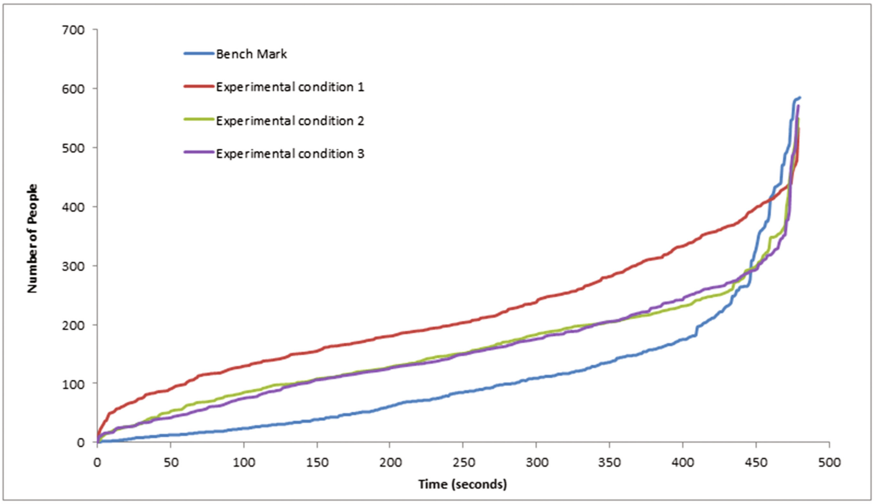


**Fig. 5.** Total arrival time pattern for one simulation run of EXODUS benchmark and IMPACT experimental conditions 1, 2 and 3.

### 3.2 Simulation Experiments Setup

**Number of Repetitions.** To determine the number of repetitions for each combination of factor and level, an evacuation scenario with the most variability was run 100 times. First, the cumulative averages and variances in evacuation time were inspected to detect the threshold number of repetitions at which evacuation time stabilised. Second, Eq. 22 below was used to find the minimum number of repetitions (56) to guarantee that the error in the outcome results is within 5% of the maximum error with a 95% confidence level. Then, 60 repetitions of each variation were run and the results presented in this Section represent the average of these 60 runs.

$$n \geq [100 \cdot Z \cdot s/r \cdot \bar{x}]^2 = 56.61599 \rightarrow 60\,\text{samples} \tag{22}$$

Whereby,

$$\begin{array}{ll} Z = \textit{confidence interval of } 95\%; & s = \textit{standard deviation}, 53.4287 \\ r = \textit{maximum error of } 5\% & \bar{x} = \textit{evacuation time average of } 100\,\textit{samples} \end{array}$$

**Outcome measures and emergence.** There are three outcome measures for each simulation experiment: (1) evacuation time, (2) total falls, and (3) response time. The evacuation time was measured as the number of seconds from the onset of the fire until all (living) passengers have evacuated. The number of falls was measured cumulatively (all falls in total in one simulation run). The individual response time was measured as the time between the onset of the fire until the passenger develops the intention to move to the exit. The reported response time is the average of all individual's response times.

Besides these outcome measures, emergence is of interest in the analyses. Emergence is the spontaneous establishment of a qualitatively new behaviour through non-linear interactions of many objects or subjects [17]. In other words, it is a behaviour observed at the group level, which cannot be directly explained from the individual behavioural rules. This could lead to unexpected findings in our simulation experiments, because the hypotheses are formulated based on individual behavioural rules, since a priori you do not always know what group level behaviour will occur. There are important crowd movement phenomena related to evacuation situations known from the literature, such as herding, the faster-is-slower-effect, and collective intelligence [16, 17]. Herding refers to a situation that is unclear and causes individuals to follow each other instead of taking the optimal route [16]. The faster-is-slower-effect refers to when, in evacuation situations, certain processes take longer at high speed; so, waiting can sometimes help competing people (competing for space) and speed up the average progress [17]. Collective intelligence, as Helbing and Johansson name it, is emergent functional behaviour of a large number of people resulting from interactions of individuals instead of individual reasoning [17].

We hope our model will create these emergent phenomena, as that would prove our model can create self-organisation [9]. Self-organisation can be defined as the spontaneous establishment of qualitatively new behaviour through non-linear interaction of many objects or subjects without the intervention of external influences. However, we do not expect our model to show emergent lane formation and the zipper effect [9]. Lane formation is a process where a number of lanes of varying width form dynamically at a corner; however, the passengers in our model do not have to go around a corner towards the exit.

Other evacuation modellers have studied behavioural and environmental effects on evacuation time as well. For example, in [20], it was found that the optimal evacuation time needs a combination of herding behaviour and the use of environmental knowledge (about the location of exits). In [47] it was found that when exits are placed symmetrically in a room, the evacuation time is shortest. It was also found that including social elements in the model (finding your group member before exiting, exiting through the entrance, and not wanting to stop but keep moving towards the exit) can make a more robust and realistic model. In [44] the social force model (Helbing social force) was implemented in a cellular automata model to simulate evacuation from a room with one exit. Arching, clogging, and the faster-is-slower-effects were found, showing that the three social forces (repulsion, friction, and attraction) can be basic reasons for complex behaviours emerging from evacuations. Also, changing the width of the door can have a large effect on evacuation time. In [11] it is shown that the crowd density around a person has an impact on that person's speed and that this is an exponential relationship, with more surrounding people reducing the person's speed. In [22] it is shown that evacuation time is not only based on the distance from the exit but also on effects such as the crowd density around the people evacuating and exit choice behaviour. In [27, 28] the social force model was applied. It was found that the wider the doors, the less faster-is-slower-effect there is, because there will be less congestion at the door. Also, the repulsive and dissipative forces seem to have the largest effects on the faster-is-slower-effect. In [19] a lattice gas model of people escaping a smoke filled room was created to replicate the findings of an experiment in which blindfolded students had to find the exit. It was found that adding exits did not shorten evacuation time, but that the evacuation process was based on herding behaviour (following the acoustics). Based on these findings from others, we expect the evacuation time to increase as crowd density increases in our model.

**Basic settings simulation experiments.** Simulation experiments with different factors and levels were designed to answer different research questions introduced in the following sections. The agent environment chosen for the simulations was a square ($20 \times 20$ m) layout of a building with four exits (top, down, left, right; main exit = down). All environmental and personal factors such as width of the doors, gender, age, and level of compliance were kept constant across simulations. Only the factors and levels stated in each experimental setup in the following sections were systematically varied. The settings that were kept similar, except the few parameters that are structurally changed to answer the current research question, are shown in Table 3 below.

**Table 3.** Basic parameter settings for the simulation experiments.

| Parameter | Setting |
|---|---|
| Familiarity | 50% (i.e. 50% of passengers are familiar with the environment) |
| Helping | Off |
| Falls | On |
| Contagion model | On |
| Percentage children | 15 (based on [29]) |
| Percentage elderly | 15 (based on [29]) |
| Percentage people travelling alone | 50 |
| Group ratios | 33-33-34 (we assume an equal distribution for group sizes) |
| Percentage females | 50% |
| Fire location | Random location, but always 3 m away from an exit and present from the 1st second |
| Cultural cluster distribution | Equal division of all passengers over all 11 clusters (9.09% of passengers per cluster) |
| Length of fall (before standing up) | 30 s |
| Start fire alarm | 180 s after the fire starts |
| Start public announcement | 20 s after the fire alarm starts |

### 3.3 Simulation Results: Effect of Falls

Table 4 shows the design of the simulation experiment to determine the effect of falling on evacuation time, total falls, and the average response time. The total number of simulation runs is based on the number of factors and levels, and number of repetitions per combination of factor and level, resulting in $3 \times 2 \times 60 = 360$ simulation runs here. The hypotheses were: (1) when falling behaviour is 'on', evacuation time will be slower than when there are no falls (because it will take extra time to fall and stand back up); (2) when falling behaviour is 'on', falls will happen, but no falls will happen when this feature is turned 'off'; (3) there will be no difference in response times for falling 'on' versus 'off' (as response time precedes evacuation movement).

**Evacuation time.** The results are shown in Fig. 6. As expected, the higher the crowd density, the slower the evacuation time. Unexpectedly, though, the evacuation time

**Table 4.** Factors and levels in the simulation experiment for falls.

| | Factor | |
|---|---|---|
| | Crowd Density | Falls |
| Level 1 | Low | On |
| Level 2 | Medium | Off |
| Level 3 | High | |

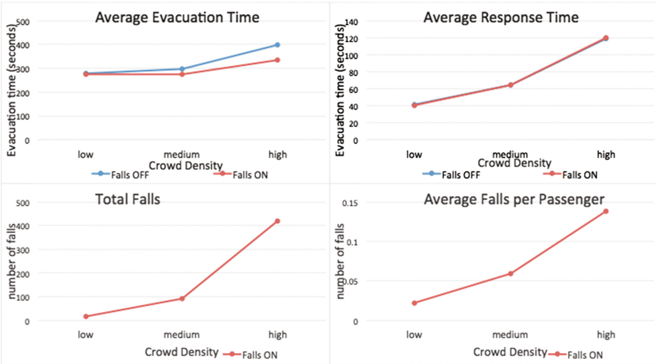


**Fig. 6.** Effect of falls on evacuation time, falls, and response time.

decreases when falls occur, compared to no falls (see Fig. 6, top left), which is the opposite of what was expected. However, this can be explained due to the fact that the evacuation of the fallen agents is delayed, thereby reducing the overall crowd congestion at exits. Essentially, then, a more phased evacuation takes place, which takes less time. In other words, this could be explained by the faster-is-slower-effect [17]. This effect reflects the observation that certain processes (in evacuation situations, production, traffic dynamics, or logistics) take more time if performed at high speed. In other words, waiting can often help to coordinate the activities of several competing units and thus speed up the overall progress. In our case, falling seems to have similar effects to waiting and speeds up the overall evacuation.

To find out if these effects could be significant, statistical analyses were performed on the data. A 2 × 3 independent ANOVA was performed on the evacuation time with Falls (with or without) and Crowd Density (low, medium, and high) as between factors. The main effect of Crowd Density was significant, $F(2, 354) = 12.96$, $p < .001$, and the main effect of Falls was approaching significance, $F(1, 354) = 3.72$, $p = .055$, but the interaction effect of Falls × Crowd Density was not significant, $F(2, 354) = 1.23$, *n.s.* Post hoc tests with Tukey HSD corrections showed that only high Crowd Density differs significantly from low and medium Crowd Density, but low and medium Crowd Density do not differ significantly: high-low, $p < .001$; high-medium, $p < .001$; low-medium, *n.s.* In conclusion, then, evacuation time seems to significantly increase for high crowd density versus low or medium crowd density, and a trend is visible for slower evacuation time without falls versus with falls.

**Total number of falls.** As expected, both the total falls and average falls per person increase as the crowd density increases, for two reasons. First, the more agents there are in the environment, the less room there is to move and so more falling occurs. Second, the more agents there are in the environment, the higher the chances of individuals falling which will increase the average rate (see Fig. 6, bottom row). A 2 × 3 independent ANOVA was performed on the Total Falls with Falls (with or without) and Crowd Density (low, medium, and high) as between factors. The main effects of Falls and Crowd Density and the interaction effect of Falls × Crowd Density were significant: $F(2, 354) = 5612.60$, $p < .001$; $F(1, 354) = 11306.25$, $p < .001$; $F(2, 354) = 5612.60$, $p < .001$, respectively. Post hoc tests with Tukey HSD corrections showed that each level of Crowd Density differs significantly from each other level: high-low, $p < .001$; high-medium, $p < .001$; low-medium, $p < .001$.

**Response time.** As expected, response time increases as crowd density increases and no significant differences were found in response time for falling behaviour ‘on’ versus ‘off’. Statistical analyses confirm these findings. A $2 \times 3$ independent ANOVA was performed on the response time with Falls (with or without) and Crowd Density (low, medium, and high) as between factors. The main effect of Crowd Density was significant, $F(2, 354) = 4773.30$, $p < .001$. There was no main effect of Falls, $F(1, 354) = .012$, *n.s.*, and no interaction effect of Falls × Crowd Density, $F(2,354) = .681$, *n.s.* Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from the other two: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

### 3.4 Simulation Results: Helping Behaviour

Table 5 shows the design of the simulation experiment to determine the effect of helping behaviour on evacuation time, falls, and response time, resulting in $3 \times 2 \times 60 = 360$ simulation runs here. The hypotheses were: (1) when people help others, the evacuation time is longer than when people do not help (because the helpers will take more time to evacuate; although only a small effect is expected); (2) when passengers help others, the number of falls will increase (because the helpers next to the fallen passengers create more obstacles; although only a small effect is expected); (3) no difference is expected in response times for helping ‘on’ versus ‘off’ (because the decision to evacuate precedes helping).

**Table 5.** Factors and levels in the simulation experiment for crowd density and helping.

| | Factor | |
|---|---|---|
| | Crowd Density | Helping |
| Level 1 | Low | On |
| Level 2 | Medium | Off |
| Level 3 | High | |

**Evacuation time.** The results are shown in Fig. 7. As expected, evacuation time increases as crowd density increases. However, unexpectedly, helping behaviour seems to reduce evacuation time for high crowd density environments slightly, but not for low to medium crowd density. This could be explained by those helping delaying their evacuation slightly and forming less congestion overall, like a phased evacuation, as happened with the falls. Essentially, people will evacuate one after another (sequentially) which creates less congestion at the doors (see Fig. 7, left). Again, this could be explained with the faster-is-slower-effect, mentioned in the explanation of falls, reducing the average evacuation time [17]. When analysing these effects statistically,

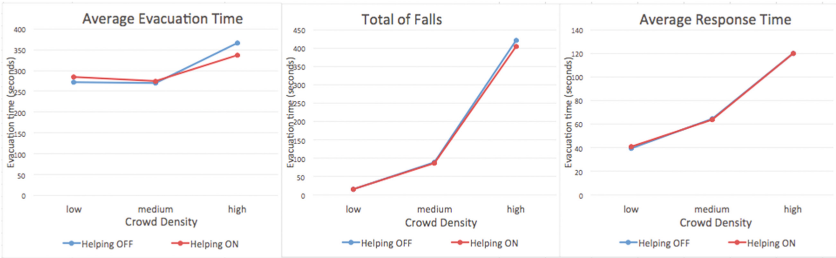


**Fig. 7.** Effect of helping behaviour on evacuation time, falls, and response time.

though, only the main effect of crowd density is significant and not the effect of helping. A 2 × 3 independent ANOVA was performed on the response time with Helping (with or without) and Crowd Density (low, medium, and high) as between factors. The main effect of Crowd Density was significant, $F(2, 354) = 22.87$, $p < .001$. However, there was no main effect of helping, $F(1, 354) = .119$, *n.s.*, and no interaction effect of Falls × Crowd Density, $F(2, 354) = 1.37$, *n.s.* Post hoc tests with Tukey HSD corrections show that only high Crowd Density differs significantly from low and medium Crowd Density, and low and medium Crowd Density do not differ significantly: high-low, $p < .001$; high-medium, $p < .001$; low-medium, *n.s.*

**Total number of falls.** The number of falls naturally increases as the crowd density increases. This increase seems similar for helping behaviour 'on' and 'off', but the difference is actually significant when tested statistically (see Fig. 7, middle). A 2 × 3 independent ANOVA was performed on the total Falls with Helping (with or without) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density, $F(2, 354) = 22.87$, $p < .001$, and Helping were significant, $F(1, 354) = 8.45$, $p < .01$, as was the interaction effect of Helping × Crowd Density, $F(2, 354) = 5.52$, $p < .01$. Post hoc tests with Tukey HSD corrections show each level of Crowd Density differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$. In conclusion, the number of falls increases both when crowd density increases and also without helping.

**Response time.** As expected, no differences are observed in the average response times for helping behaviour 'on' and 'off', only an effect of crowd density which statistical analyses confirm. A 2 × 3 independent ANOVA was performed on the Response Time with Helping (with or without) and Crowd Density (low, medium and high) as between factors. The main effect of Crowd Density was significant, $F(2, 354) = 5162.73$, $p < .001$, while neither the main effect of Helping, $F(1, 354) = .416$, *n.s.*, or the interaction effect of Helping × Crowd Density were significant, $F(2, 354) = .798$, *n.s.* Post hoc tests with Tukey HSD corrections show each level of Crowd Density differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$ (see Fig. 7, right).

### 3.5 Experimental Results: Social Contagion and Familiarity

Table 6 shows the experimental design of the simulation experiment to determine the effect of social contagion and familiarity on evacuation time, falls, and response time, resulting in $3 \times 3 \times 2 \times 60 = 1080$ simulation runs here. The hypotheses were: (1) evacuation time will be faster with social contagion than without (because people will still find out from others there is a fire, even when not observed personally); (2) when crowd density increases, there will be more falls; (3) when there is social contagion, there will be fewer falls (because without it, more people will find out the situation is dangerous through the fire alarm, which means more people will evacuate simultaneously, thereby falling more); (4) response time will be faster with social contagion than without (because people who do not observe the fire themselves are informed faster by others); (5) response time will be faster the more familiar people are with the environment (because taking the nearest exit in combination with social contagion will speed up the response time, spreading the 'news' faster than when people all take the same exit); and finally (6) the higher the crowd density, the slower the response time.

**Table 6.** Factors and levels in the simulation experiment for social contagion and familiarity

| | Factor | | |
|---|---|---|---|
| | Crowd Density | Familiarity | Social Contagion |
| Level 1 | Low | 0% | On |
| Level 2 | Medium | 50% | Off |
| Level 3 | High | 100% | |

**Evacuation time.** The results are shown in Fig. 8. As expected, with social contagion there is a decrease in evacuation time compared to without, and the more familiar people are with the environment, the faster their evacuation time (see Fig. 8, top row), which statistical analyses confirmed. The social contagion of mental and emotional states is a form of collective group decision making or collective intelligence [17]. It is also related to herding, as individuals are 'infected' with other's decisions and follow them when their own intentions are not as strong as those of others around them. [16]. A $2 \times 3$ independent ANOVA was performed on Evacuation Time with Social Contagion (with or without) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Social Contagion and the interaction effect of Social Contagion $\times$ Crowd Density were significant: $F(2, 354) = 133.81$, $p < .001$; $F(1, 354) = 237.76$, $p < .001$; $F(2, 354) = 4.35$, $p < .05$, respectively. Post hoc tests with Tukey HSD corrections show each level of Crowd Density differs significantly from each other: low-medium, $p < .05$; medium-high, $p < .001$; low-high, $p < .001$. A $3 \times 3$ independent ANOVA was performed on the Evacuation Time with Familiarity (0%, 50%, or 100%) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Familiarity and the interaction effect of Familiarity $\times$ Crowd Density were significant: $F(2, 354) = 125.83$; $p < .001$, $F(1, 354) = 23.16$, $p < .001$; $F(2, 354) = 31.10$, p < .001, respectively. Post hoc tests

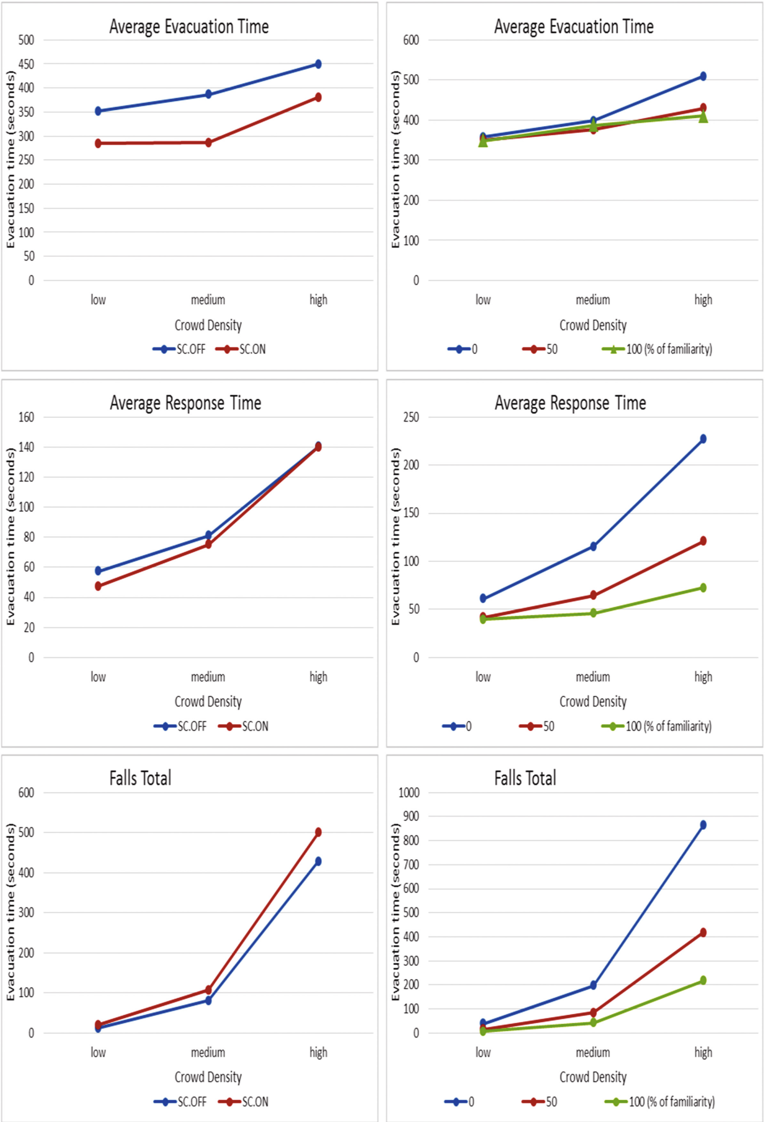


**Fig. 8.** Effects of social contagion (left column) and familiarity (right column) on evacuation time, response time, and falls.

with Tukey HSD corrections show each level of Crowd Density differs significantly from each other: low-medium, $p < .05$; medium-high, $p < .001$; low-high, $p < .001$. For Familiarity, only 0% familiarity differs significantly from 50% and 100%, but not 50% from 100%: 0%–50% $p < .05$; 50%–100% *n.s.*; 0%–100% $p < .05$.

**Total number of falls.** As expected, the number of falls is lower with social contagion than without. This can be explained by people starting to evacuate earlier, spreading the evacuation across the simulation time. Consequently, there are fewer collisions among passengers, which result in fewer falls. Familiarity shows the same effect: the more familiar the crowd members are with the environment, the more distributed among the exits they are, which consequently leads to fewer collisions and falls (see Fig. 8, bottom row). Statistical analyses confirmed these interpretations. A 2 × 3 independent ANOVA was performed on the Total Falls with Social Contagion (with or without) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Social Contagion and the interaction effect of Social Contagion × Crowd Density were significant: $F(2, 354) = 732.98$, $p < .001$; $F(1, 354) = 11.88$, $p < .01$; $F(2, 354) = 3.42$, $p < .05$. Post hoc tests with Tukey HSD corrections show each level of Crowd Density differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$. A 3 × 3 independent ANOVA was performed on the Total Falls with Familiarity (0%, 50%, or 100%) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Familiarity and the interaction effect of Familiarity × Crowd Density were significant: $F(2, 354) = 17290.13$; $p < .001$; $F(1, 354) = 6227.45$, $p < .001$; $F(2, 354) = 3062.52$, $p < .001$. Post hoc tests with Tukey HSD corrections show each level of Crowd Density and Familiarity differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$; 0%–50%, $p < .001$; 50%–100%, $p < .001$; 0%–100%, $p < .001$.

**Response time.** As expected, response time increases as crowd density increases and with social contagion the increase is lower than without social contagion. Similarly, the more familiar people are with their environment, the less the response time increases as crowd density increases. This is explained by familiarity distributing people over the available exits, which helps to convey the fear and belief of danger with social contagion to others who start to evacuate early (see Fig. 8, middle row). Statistical analyses confirmed the two main effects of crowd density and social contagion. A 2 × 3 independent ANOVA was performed on Response Time with Social Contagion (with or without) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density, $F(2, 354) = 410.46$, $p < .001$, and Social Contagion were significant, $F(1, 354) = 4.46$, $p < .05$, while the interaction effect of Social Contagion × Crowd Density was not significant, $F(2, 354) = 1.16$, *n.s.* Post hoc tests with Tukey HSD corrections show each level of Crowd Density differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$. A 3 × 3 independent ANOVA was performed on Response Time with Familiarity (0%, 50%, or 100%) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Familiarity and the interaction effect of Familiarity × Crowd Density were significant: $F(2, 354) = 11785.94$, $p < .001$; $F(1, 354) = 10311.63$, $p < .001$; $F(2, 354) = 2334.88$, $p < .001$, respectively. Post hoc tests with Tukey HSD corrections show each level of Crowd Density and Familiarity differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$; 0%–50%, $p < .001$; 50%–100%, $p < .001$; 0%–100%, $p < .001$.

### 3.6 Groups

Table 7 shows the design of the simulation experiment to determine the effect of group size on evacuation time, falls, and response time, resulting in $3 \times 4 \times 60 = 720$ simulation runs. The hypotheses were: (1) the more people who travel alone, the faster the evacuation time (because people will move faster by themselves); (2) the bigger the groups, the slower the evacuation time (although this is expected to be a small effect); (3) the more people who travel alone, the fewer falls (because groups form more congestion; although this is expected to be a small effect); (4) the larger the groups, the more falls (because of more congestion); (5) the more people who travel alone, the faster the response time (because people can evacuate faster); and (6) the bigger the groups, the slower the response time (although this is expected to be a small effect).

**Table 7.** Factors and levels in the simulation experiment for groups

| | Factor | |
|---|---|---|
| | Crowd Density | Travelling Alone |
| Level 1 | Low | 100% |
| Level 2 | Medium | 0% (only groups of 2 adults) |
| Level 3 | High | 0% (only groups of 3 adults) |
| Level 4 | | 0% (only groups of 4 adults) |

**Evacuation time.** The results are shown in Figs. 9 and 10. As expected, as crowd density increases, evacuation time becomes slower. Unexpectedly, though, it seems that people travelling alone and in groups of three are slower to evacuate than groups of two and four. Indeed, groups of four evacuate the fastest and people travelling alone are actually slowest (Fig. 9). Statistical analysis confirms this interpretation. A $4 \times 3$ independent ANOVA was performed on Evacuation Time with Group Size (1, 2, 3, and 4) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Group Size, and the interaction effect of Group Size $\times$ Crowd Density were significant: $F(2, 354) = 22643.44$, $p < .001$; $F(3, 354) = 137.15$, $p < .001$; $F(6, 354) = 3.70$, $p < .001$. Post hoc tests with Tukey HSD corrections show

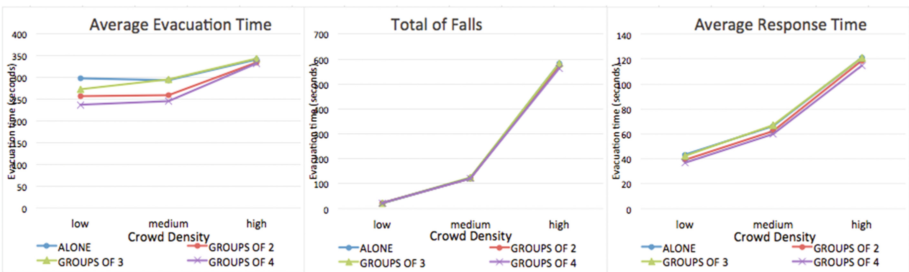


**Fig. 9.** Effects of groups on evacuation time, falls, and response time.

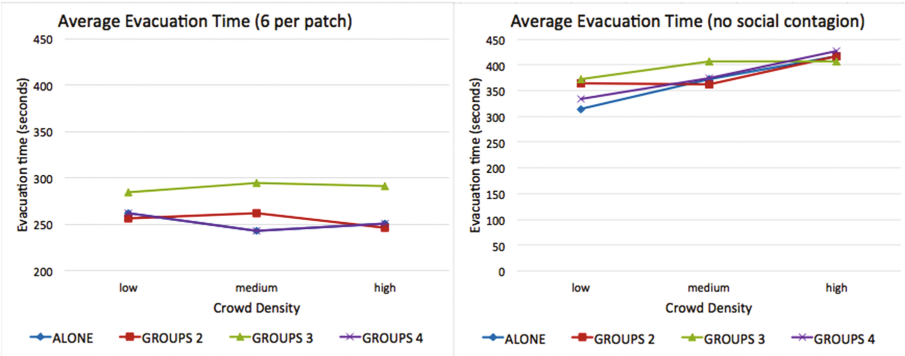


**Fig. 10.** Effects of groups on evacuation time with a maximum travel capacity of six people per $m^2$ (left) and without social contagion (right).

that only high Crowd Density differs significantly from low and medium Crowd Density: high-low, $p < .001$; high-medium, $p < .001$; low-medium, *n.s.* For Group Size, these tests show that a lone person does not differ from groups of 3, and groups of 2 do not differ from groups of 4; however, all others differ significantly from each other: 1–2, $p < .001$; 1–3, *n.s.*; 1–4, $p < .001$; 2–3, $p < .01$; 2–4, *n.s.* In conclusion, evacuation time increases when crowd density increases and decreases for groups of 4 and 2 versus groups of 3 or 1.

This is unexpected and seems to not be an effect of speed, because all group sizes have the same number of falls. Therefore, it does not seem to be a faster-is-slower-effect [17]. When inspecting the average speed during simulations, it was confirmed that they did not differ for group sizes. Also, the outcome measures did not differ significantly for different numbers of children and elderly, which could influence the average speeds of the groups. However, what could explain groups of four being faster than people travelling alone is social contagion in combination with moving through space. With social contagion, or collective intelligence, groups can 'infect' each other faster with emotions and beliefs, compared to people travelling alone, which is beneficial for evacuation time. Moving through space is implemented with a maximum of 8 passengers per patch (square metre), meaning lone passengers and groups of 2 and 4 can always use a patch to its maximum capacity, but groups of 3 can only fit a maximum of two groups (6 passengers) per patch at one time step. This means groups of 3 are a little disadvantaged, since groups of 1, 2, and 4 can always move around in space with maximum capacity. That could explain why groups of three and people alone are slowest and groups of 2 and 4 are fastest. We have tested this by running similar simulation experiments like this one, but then (1) without social contagion, and (2) with a maximum capacity of 6 people per square metre. The expectation is that (1) without contagion, groups of 3 will be slowest versus groups of 1, 2 and 4, and (2) with a maximum capacity of 6 people per square metre, groups of 4 will be slowest compared to people travelling alone and groups of 2 and 3. As expected, without social contagion, groups of 3 are slowest in evacuation time (see Fig. 10). No effects of falls and response time were observed in this experiment. Unexpectedly, groups of 3 are not the fastest with a maximum capacity of 6 per square metre, but again the slowest. This means that social contagion is only part of the explanation for groups being slower to evacuate than people travelling alone. We cannot find more explanations for this in the literature because (1) the impact of groups on crowd dynamics is still largely unknown [24, 31], and (2) we have not modelled group formations, such as in [24], that could influence the crowd dynamics. We have chosen to model a group as moving through space as a 'square' group, with all members moving from patch (square metre) to patch simultaneously. So, group formations are no explanation either. However, social contagion is part of the effect of groups of 2 and 4 being faster than people travelling alone or in groups of 3.

**Total number of falls.** As crowd density increases, the number of falls increase; although no significant differences were found between group sizes, as expected. Statistical analysis confirmed this interpretation of the graph. A $4 \times 3$ independent ANOVA was performed on Total Falls with Group Size (1, 2, 3, and 4) and Crowd Density (low, medium, and high) as between factors. The main effect of Crowd Density was significant, $F(2, 354) = 24048.28$, $p < .001$, but the main effect of Group Size, $F(3, 354) = 1.39$, *n.s.*, and the interaction effect of Group Size $\times$ Crowd Density were not significant, $F(6, 354) = 1.93$, *n.s.* Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

**Response time.** As crowd density increases, response time increases. Although no significant differences between group sizes were expected, statistical analysis showed that groups of 2 and 4 are faster in their response time than groups of 1 and 3. This seems plausible as it is similar with the evacuation time, which both can be explained by the social contagion effects. A $4 \times 3$ independent ANOVA was performed on Response Time with Group Size (1, 2, 3, and 4) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density, $F(2, 354) = 9634.55$, $p < .001$, and Group Size were significant, $F(3, 354) = 43.73$, $p < .001$, and the interaction effect of Group Size $\times$ Crowd Density was not, $F(6, 354) = .467$, *n.s*. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$; and group size 1 and 3 do not differ significantly, while the other group sizes do: 1–2, $p < .001$; 1–3, *n.s.*; 1–4, $p < .001$; 2–3, $p < .001$; 2–4, $p < .001$; 3–4, $p < .001$. Taking all these results into account, it seems that social contagion is the biggest cause for the group effects.

### 3.7 Age

Table 8 shows the design of the simulation experiment, resulting in $3 \times 2 \times 60 = 360$ simulation runs here. The hypotheses were: (1) elderly people have slower evacuation times, compared to adults (because elderly people move slower); (2) there will be no differences in number of falls between adults and elderly people; (3) there will be no differences in response time between adults and elderly people.

**Table 8.** Factors and levels in the simulation experiment for age

| | Factor | |
|---|---|---|
| | Crowd Density | Age |
| Level 1 | Low | Travelling alone 100% adults |
| Level 2 | Medium | Travelling alone 100% elderly |
| Level 3 | High | |

**Evacuation time.** The results are shown in Fig. 11. As crowd density increases, so does evacuation time. As expected, elderly people seem to be slower in evacuating than adults, most likely due to their slower movement. In this experiment, all passengers are elderly or adults exclusively, so the exact same effects are there with the elderly as with adults. For instance, there is no faster-is-slower-effect [17] here for age, because that would require differences in speed within the same simulation run. So, in this case, faster speed does mean faster evacuation. Here, the faster-is-slower-effect was present for the adults by themselves, but as a result of falls, again. However, the elderly did not fall based on their slower speeds, which in turn prevented a faster-is-slower-effect for them based on falls (see Fig. 11). Indeed, statistical analysis showed there was an effect of age. A 2 × 3 independent ANOVA was performed on Evacuation Time with Age (adult, elder) and Crowd Density (low, medium, and high) as between factors. Both the main effects of Crowd Density, $F(2, 354) = 35.40$, $p < .001$, and Age were significant, $F(1, 354) = 3.20$, $p < .001$, but the interaction effect of Age × Crowd Density was not significant, $F(2, 354) = .359$, *n.s.* Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

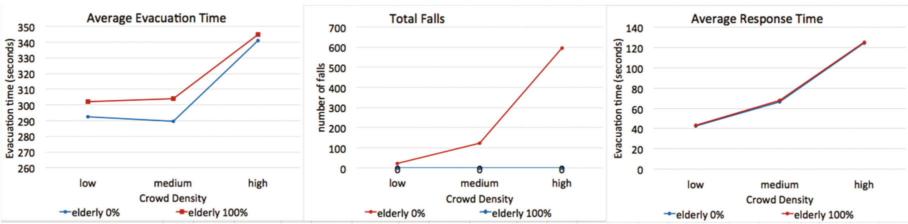


**Fig. 11.** Effects of age (speed) on evacuation time, falls, and response time

**Total number of falls.** As expected, as crowd density increases, the number of falls increases. Unexpectedly and very interestingly, elderly people have no falls and the falls of the adults increase as crowd density increases. No falls for elderly people seems unrealistic in real life, however, because elderly people should be more prone to falling than adults. The explanation for this finding is based on how falls are implemented in this model. Currently, they are based on the speed of the passengers and their age is not taken into account, so this could be improved in a future version on the IMPACT model. Discounting age, based on speed alone it makes sense that passengers who move slower have fewer falls (see Fig. 11). Statistical analysis confirmed these interpretations of the graphs. A 2 × 3 independent ANOVA was performed on Total Falls with Age (adult, elder) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density, $F(2, 354) = 13245.73$, $p < .001$, and Age were significant, $F(1, 354) = 26056.94$, $p < .001$, and the interaction effect of Age × Crowd Density was also significant, $F(2, 354) = 13245.73$, $p < .001$. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

**Response time.** As expected, as crowd density increases, response time becomes slower. Also, as expected, the response time does not differ significantly between the elderly and adults (see Fig. 11). Statistical analysis confirmed this interpretation of the graph. A 2 × 3 independent ANOVA was performed on Response Time with Age (adult, elder) and Crowd Density (low, medium, and high) as between factors. The main effect of Crowd Density was significant, $F(2, 354) = 5507.43$, $p < .001$; however, the main effect of Age, $F(1, 354) = 2.52$, *n.s.*, and the interaction effect of Age × Crowd Density were not significant, $F(2,354) = .03$, *n.s.* Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

### 3.8 Compliance

Table 9 shows the design of the simulation experiment to determine the effect of compliance on evacuation time, number of falls, and response time, resulting in 3 × 2 × 60 = 360 simulation runs here. The hypotheses were: (1) evacuation time is faster for 100% compliance than 0% compliance; (2) more falls will happen with 100% compliance compared with 0% (because people will evacuate faster resulting in crowding and so more falls); (3) response time will be faster for 100% compliance compared to 0% (because people will decide to evacuate faster). This simulation experiment was also run for adults and the elderly, both female and male. With the current parameter settings, no significant differences between females and males or adults and the elderly were found, meaning that the difference in the current compliance level settings for gender and age do not create differences in the actions (see Sect. 2.1 for these settings). Therefore, to find the effect of the compliance parameter, this experiment was set up comparing a low with a high level. For a maximum effect of compliance, levels 1 and 0 were preferred, but the simulation does not run with

**Table 9.** Factors and Levels in the Simulation Experiment for Compliance

| | Factor | |
|---|---|---|
| | Crowd Density | Compliance |
| Level 1 | Low | Compliance level 0.1 (only male adults) |
| Level 2 | Medium | Compliance level 1 (only male adults) |
| Level 3 | High | |

compliance set to 0, since the passengers will not move then. Compliance set to 0.001 or 0.01 resulted in one simulation run taking multiple days. With the value of 0.1 there is still a large effect of compliance to be seen and the simulation runs were practically feasible to run, so this level was selected for the experiment.

**Evacuation time.** Results are shown in Fig. 12. As expected, as crowd density increases, evacuation time increases, and high compliance results in faster evacuation time than low compliance. A 2 × 3 independent ANOVA was performed on Evacuation Time with Compliance (low, high) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Compliance and the interaction effect of Compliance × Crowd Density were all significant: $F(2, 354) = 33.75$, $p < .001$; $F(1, 354) = 3092.49$, $p < .001$; $F(2,354) = 6.65$, $p < .001$, respectively. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .01$; medium-high, $p < .001$; low-high, $p < .001$.

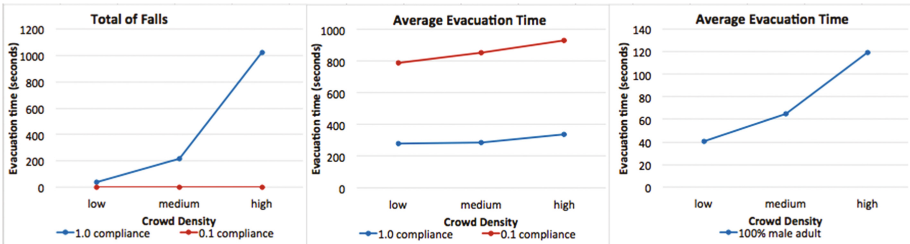


**Fig. 12.** Effects of compliance on evacuation time, falls, and response time.

**Total number of falls.** As expected, more falls happen as crowd density increases and when there is high compliance versus low compliance. No falls happened in the low compliance simulation runs, though, which can be explained by the slower speed that is a result of low compliance. A 2 × 3 independent ANOVA was performed on Total Falls with Compliance (low, high) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Compliance and the interaction effect of Compliance × Crowd Density were all significant: $F(2, 354) = 13110.60$, $p < .001$; $F(1, 354) = 25825.15$, $p < .001$; $F(2,354) = 13110.60$, $p < .001$, respectively. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

**Response time.** Response times for male adults are shown in Fig. 12, which do not significantly differ from female adults and the elderly, as expected, and show a similar pattern for a high compliance level. The response time for the low compliance level did not register in the simulations; that is why the response time for male adults with a compliance level of 0.89 are shown and analysed. An independent one-way ANOVA was performed on the Response Time of male adults with Crowd Density (low, medium, and high) as a between factor. The main effect of Crowd Density was significant, $F(2, 717) = 397678.37$, $p < .001$. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

### 3.9 Environment

Table 10 shows the design of the simulation experiment to determine the effect of room type on evacuation time, falls, and response time, resulting in $3 \times 6 \times 60 = 1080$ simulation runs here. The hypotheses were: (1) evacuation time increases faster in the rectangular room than the square room (because people take more time to reach the exits); (2) the number of falls is higher in the rectangular room (because people use more steps to reach the exits); (3) response time is slowest in the rectangular room (because in larger rooms there is less chance of observing the fire).

**Table 10.** Factors and Levels in the Simulation Experiment for Environment

| | Factor | |
|---|---|---|
| | Crowd Density | Room type |
| Level 1 | Low | Type 1 (square, 20 × 20 m) |
| Level 2 | Medium | Type 2 (rectangle 20 × 40 m) |
| Level 3 | High | |

**Evacuation time.** Results are shown in Fig. 13. As expected, evacuation time increases as crowd density increases, although this only happened for high crowd density and not low and medium densities (see Fig. 13, left). Statistical tests confirm this interpretation of the graph. A 2 × 3 independent ANOVA was performed on Evacuation Time with Room Type (square or rectangle) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Room Type and the interaction effect of Room Type × Crowd Density were all significant: $F(2, 354) = 104.97$, $p < .001$; $F(1, 354) = 443.17$, $p < .001$; $F(2,354) = 35.07$, $p < .001$, respectively. Post hoc tests with Tukey HSD corrections show that high

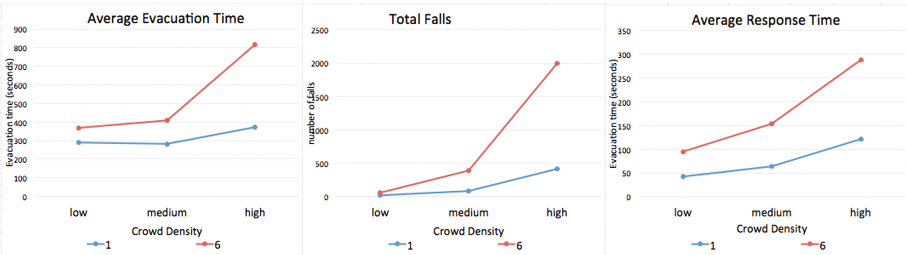


**Fig. 13.** Effects of room type on evacuation time, falls, and response time.

Crowd Density differs significantly from low and medium, but low and medium do not differ significantly: low-medium, *n.s.*; medium-high, $p < .001$; low-high, $p < .001$.

**Total number of falls.** As crowd density increases, so do the number of falls. The number of falls also increase faster in the larger room than in the smaller room.

**Table 11.** Effects of Socio-Cultural, Cognitive, and Emotional Elements on Evacuation Time

| Model element | Variations | Average evacuation time (seconds) | Difference from benchmark (seconds) | Relative difference from benchmark (percentage) |
|---|---|---|---|---|
| Falls | Off (benchmark) | 324.31 | | |
| | On | 293.51 | −30.8 | −9.5% |
| Helping behaviour | Off (benchmark) | 302.57 | | |
| | On | 298.86 | −3.71 | −1.2% |
| Social Contagion | Off (benchmark) | 396.12 | | |
| | On | 317.27 | −78.85 | −20.0%** |
| Familiarity | 0% of passengers familiar with environment (benchmark) | 412.47 | | |
| | 50% of passengers familiar with environment | 385.38 | −27.09 | −6.6%*** |
| | 100% of passengers familiar with environment | 381.52 | −30.95 | −7.5%*** |
| Groups | People travelling alone (benchmark) | 311.29 | | |
| | Groups of two | 282.95 | −28.37 | −9.1%*** |
| | Groups of three | 303.87 | −7.42 | −2.4%*** |
| | Groups of four | 217.79 | −93.5 | −30.0%*** |
| Age | All adults (benchmark) | 307.6 | | |
| | All elderly people | 316.83 | +9.23 | +3.0%*** |
| Compliance | High compliance (1.0) (benchmark) | 301.17 | | |
| | Low compliance (0.1) | 856.03 | +554.86 | +184.2%*** |
| Environment | Small square room (20 × 20 m) (benchmark) | 313.07 | | |
| | Big rectangle room (20 × 40 m) | 530.86 | +217.79 | +705.0%*** |

Significant main effect: $^{**}p < .01$, $^{***}p < .001$.

Note that the increase in falls is not due to more space in the rectangular room and more space to move (faster) towards the exits, as the crowd densities are kept the same relative to the total square metres of the room. Rather, a longer pathway (more steps towards the exit) increases the chance of falling (see Fig. 13, middle). Statistical analysis confirms this interpretation of the graph. A 2 × 3 independent ANOVA was performed on Total Falls with Room Type (square or rectangle) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Room Type and the interaction effect of Room Type × Crowd Density were all significant: $F(2, 354) = 2100.66$, $p < .001$; $F(1, 354) = 1524.03$, $p < .001$; $F(2, 354) = 893.53$, $p < .001$. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

**Response time.** As expected, the response time is slower in the rectangular room than in the square room and also increases as crowd density increases (see Fig. 13, right). Statistical analysis confirms this interpretation of the graph. A 2 × 3 independent ANOVA was performed on Response Time with Room Type (square or rectangle) and Crowd Density (low, medium, and high) as between factors. The main effects of Crowd Density and Room Type and the interaction effect of Room Type × Crowd Density were all significant: $F(2, 354) = 5648.72$, $p < .001$; $F(1, 354) = 11279.66$, $p < .001$; $F(2, 354) = 1003.42$, $p < .001$, respectively. Post hoc tests with Tukey HSD corrections show that each level of Crowd Density differs significantly from each other level: low-medium, $p < .001$; medium-high, $p < .001$; low-high, $p < .001$.

### 3.10 Comparing Results: Influence of Socio-Cultural, Cognitive, and Emotional Elements

In this section, the effects of the socio-cultural, cognitive, and emotional elements in the model will be compared to identify how much each element influences the total evacuation time. In this way, the added value of each element can be interpreted. Of course, this is in the case of the empty environment studied in the simulation experiments, where only the human behaviour is studied during evacuation. In real life, the effects of the socio-cultural, cognitive, and emotional elements will be combined with environmental influences, such as obstacles, stairs, corridors, lanes, and pathways. Table 11, above, shows the effects of each model element (e.g. falling, helping, social contagion) on the total evacuation time in seconds and is expressed as a percentage of relative difference compared to the benchmark. The relative differences of each model element range from reducing the total evacuation time by 30% to increasing it by 705%. Most notable are the decreases in evacuation time caused by social contagion of 20%, familiarity of between 6.6% and 7.5%, and travelling in groups of between 2.4% and 30%. Compliance and environment type also have a very large effect on the evacuation time – increasing it by 184.2% and 705%, respectively – but these two effects are harder to compare in size with the others in the table, because the parameter settings of compliance and the sizes of the environment types made the effect very large. The other effects are comparable, though, because the human behaviour all takes place in the same environment and the settings chosen are realistic. In conclusion, the socio-cultural, cognitive, and emotional elements that can be compared – falling, helping, social contagion, familiarity with environment, group sizes, and age – have an effect on evacuation time between decreasing it by 30% to increasing it by 3%.

## 4 Conclusion and Discussion

The aim of this research was to create and validate an evacuation simulation that includes socio-cultural, cognitive, and emotional factors in response to the need for more realistic crowd models that incorporate psychological and social factors. The development of the model drew on insights from social and cross-cultural psychology, interviews with crisis management experts, and was based on scientific findings and literature. The model was validated against data from an evacuation drill simulated by the existing EXODUS evacuation model [13, 26]. Our IMPACT model was compared with this benchmark on multiple outcome measures and results showed that, on all measures, the IMPACT model was within or close to the prescribed boundaries, thereby establishing its validity.

Next, multiple simulation experiments were run to answer research questions concerning the effects of the socio-cultural, cognitive, and emotional elements in the model on evacuation time, total number of falls, and response time. Important findings are that emergent effects, such as the faster-is-slower-effect [17], were found in our results in new forms: as effects of falling, helping, social contagion, and familiarity with the environment. For instance, both falling behaviour and helping (in high crowd density) led to faster evacuation times. The explanation is that falling and helping create a more phased evacuation – as the delays they cause effectively stagger the evacuation and reduce congestion – that results in a faster overall process. Moreover, as expected, social contagion also creates faster evacuation times, because information about the need to evacuate spreads faster than without social contagion. It also unexpectedly led to less falls, which again can be explained by the faster-is-slower-effect. Again, like with falls and helping, people are more phased in their evacuation, meaning less congestion at the bottlenecks (the exits) and therefore less falls. Furthermore, the more people are familiar with the environment: (1) the faster the evacuation time, (2) the fewer the falls, and (3) the faster the response time. These results are a combination of a phased evacuation (meaning less congestion and fewer falls, and therefore a faster-is-slower-effect resulting in faster evacuation time), less congestion (more people spread through the environment going to the nearest exits instead of all taking the same exit, meaning fewer falls), and social contagion (the decision to evacuate can spread faster, meaning faster response times and evacuation times). Groups also showed an interesting effect. The current model suggests it is actually faster to evacuate in groups than alone. This was not based on speed, and therefore not a faster-is-slower-effect, but partly based on social contagion (collective intelligence and herding). The impact of groups on crowd dynamics is still largely unknown [24] and we have not modelled group formations, such as in [24], that could influence the crowd dynamics. Rather, we had chosen to model a group as moving through space as a 'square' group, with all members moving from patch (square metre) to patch simultaneously. The effect of group formations would therefore need further research with the current model.

The faster-is-slower-effect was not found when comparing age groups, however, as the elderly evacuated more slowly than adults although moving more slowly. The reason for the faster-is-slower-effect not being present here for age is that it would require differences in speed within the same simulation run. In this model, however, all passengers within a simulation were either exclusively fast (adults) or slow (elderly people), which meant that faster speed means faster evacuation here. For adults by themselves the faster-is-slower-effect was present, but then as a result of falls. The elderly did not fall due to their slower speeds, which in turn prevented a faster-is-slower-effect when looking at falls instead of speed. The elderly did not fall once in the simulation which is not realistic in real life, since elderly people are more prone to falling. The current implementation of falling is based on speed alone and therefore needs to be improved to also take age into account. With a high level of compliance, people evacuate faster than with a low level of compliance, as expected. The current settings of compliance levels do not make enough differentiation between different ages and genders to have an effect. The simulation experiment showed that the compliance parameter can have an effect, but not with the current model settings. It needs to be decided if this parameter can be omitted or if new parameter settings for different ages and genders can be calculated from new data. Finally, in the smaller square room ($20 \times 20$ m), evacuation was faster than in the larger rectangular room ($20 \times 40$ m). Also, in the smaller square room there were fewer falls and a faster average response time than expected. Essentially, taking more steps towards the exit means more chance of falling.

Comparing all simulation results together, the socio-cultural, cognitive, and emotional elements have an effect from reducing evacuation time by 30% through to increasing it by 3% when the following model elements are considered: falling, helping, social contagion, familiarity with environment, group sizes, and age. However, the parameter settings of compliance and the sizes of the environment types made these effects very large (increasing evacuation time up to 705%) and are therefore left out in this comparison. Overall, this demonstrates that including socio-cultural, cognitive, and emotional elements in evacuation models is both feasible and vital, as they can influence evacuation time by up to 30%. Of course, this is only based on our experiments in an empty square room, where there is no interaction with environmental features such as obstacles, corridors, counterflows, stairs, and others. Therefore, this (maximum) 30% effect on evacuation time should be seen as a 'pure' effect of the socio-cultural, cognitive, and emotional elements in the model, without these additional environmental influences.

The strengths of this research are the inclusion of psychological and socio-cultural aspects in the crowd simulation model, based on research literature and support from stakeholders. Furthermore, the statistical analyses of the experimental results strengthen the interpretations. The current weaknesses of this work are that not every socio-cultural, cognitive, and emotional parameter that was identified during the development of the model is yet implemented to test, such as passengers' disabilities. Conversely, though, the more parameters in the model, the more complex it becomes, and the more difficult it is to analyse and interpret all the results, so there are also benefits to this. Furthermore, the results of the simulations cannot be taken for granted and they will naturally remain estimations. However, because the simulations are based on sufficient background literature, and research and interaction with stakeholders, we believe them to be sound estimations. Moreover, the work limits itself to making predictions about the influence of human behaviour on the evacuation process. All the socio-cultural, emotional, and cognitive effects were tested in an empty room with four exits. In real life, these effects would be combined with the influences of the environment itself, such as corridors, number of exits, stairs, and obstacles. This research could therefore be extended by investigating the combined effect of these elements with the environment, like in [42]. Also, a very important phenomenon – counterflow – was not modelled here. In the current model, all passengers can always take their own pathway towards an exit and do not have to cross or overtake others in the simulation. Therefore, the effects of counterflows are not modelled. Also, it was assumed that when people fall they can stand up again after a while. In reality, people could be trampled on or injure themselves and therefore not be able to stand up again. Consequently, the way we modelled falling behaviour here is just a first step towards studying this effect. However, it is difficult to model, since there is no research conducted yet (to the knowledge of the authors) that indicates what the chances of falling are in certain crowd densities and environments, and also how long it takes to stand back up. Future work consists of developing the model further to simulate realistic transport hub environments and extending the pathfinding behaviour with more heuristics.

To conclude, we reiterate three points that summarise our findings and implications: (1) our model is a realistic evacuation simulation, validated in comparison with an established model and demonstrating well-known emergent effects, such as the faster-is-slower-effect; (2) we would recommend that evacuation simulation modellers include socio-cultural, emotional, and cognitive elements in future models, based on the substantial effect sizes found here (reducing evacuation time by up to 30%), especially social contagion; (3) cultural and social diversity can be beneficial to evacuation as they create more phased evacuations, which create an overall benefit from the faster-is-slower-effect. Further implications are that transport operators, emergency managers, and prevention professionals can use these kinds of agent-based models to predict outcomes and inform decision making when designing systems [5]. These models could also be used to support periodic safety and security risk assessments and mandatory risk assessments when environments or procedures change, and/or when new communication processes or technologies are implemented. Also, policy makers could use these models to support the identification of mandatory regulations and standards with respect to communication for emergency prevention and management. In conclusion, these are promising developments and the incorporation of further psychological insights into crowd simulations will help enhance the realism of these models and the accuracy with which they can predict and prevent crowd disasters.

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