An Agent-Based Model for Crowd Evacuation in Situations with Panic

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Abstract

In this project we made an Agent-Based Model of the social force model. We extended it to include panic to research the crowd behaviour during emergency evacuations. We extended the model further with agents assuming different strategies: *'nearest exit', 'hesitator'* and *'follow the leader'*. We experimented with these strategies, focusing on evacuation time and pedestrian flow. We found the first strategy to perform the best. We further performed experiments with varying door sizes and population, where sufficiently large door size is particularly important. Lastly, we performed a local and global sensitivity analysis on several of our parameters.

1 Introduction

There have been many occasions where the crowd behaviour during panic situations has led to disastrous events (Helbing, Farkas, Molnar, & Vicsek, 2002). Many of these instances are during emergency evacuation of a building, where a jam at the door is created and where people are either crushed to death, trampled or do not get out in time due to the inefficient movement of the crowd. These evacuations may occur due to fires, attackers, or a triggered alarm. In all these scenarios, the aim is to clear the building as soon as possible. Yet, crowd behaviour, especially when people are panicked, can lead to inefficiency. Thus, it is thus important to look into how this inefficiency may be minimized and understanding which behavioural rules cause this behaviour.

To experiment with this we modelled the behaviour, as real life experiments would be unethical. Our model extends the social force model with panic and different (local) strategies. In this report we use Agent-Based Modelling (ABM) to simulate crowd behaviour during situations where panic occurs. We have chosen for ABM, because we are interested how individual decisions, affected by panicked behaviour in a stressful environment, influence the evacuation. Further, evacuation of a building has a clear spatial aspect and behaviour of our agents depends on local interactions between them in the model space. Lastly, we wanted to model the heterogeneity of our agents. All these factors make an agent-based model the most suitable type of model.

This report follows the ODD+D protocol to describe our ABM model, starting with a short overview of the model, followed by the design concepts and concluding with the details of our implementation and experiments. Hereafter, the results of our experiments and sensitivity analysis are discussed. Finally, the report is summarised in a short conclusion.

2 Model Description

2.1 Overview

2.1.1 Purpose

The purpose of our study is understanding why the collective behaviour we observe occurs and how chosen parameters values impact the outcome of the model, measured in outflow and evacuation time. It is designed to understand the behaviour and to see which parameters are most influential for the emergent behaviour and even more importantly the model outcome, i.e. the time it takes to evacuate the room completely.

2.1.2 Entities, State variables and Scales

The entities in our model are our agents, consisting of humans in a room. Further, there are two types of objects, walls and exits. Walls are avoided and exits are the spaces (doors) between the walls where the agents can exit the room. Our model is not subject to exogenous factors. The emergency that is triggered at the beginning of our model is not actually incorporated in our model, so negative effects of smoke or deaths by attackers are not included.

The attributes of our agents are defined in Table 1. The agents are heterogeneous in a few aspects: their *mass, radius* and *reliance on what is in front of them.* Each attribute is initialised by randomly and uniformly drawing a sample from the allowed range. The allowed ranges for each attribute are shown in Table 1. Further, at the beginning of the model the agents are initialised with a random position and a random velocity, which has a random direction with a speed of 0 to 0.5 m/s.

The last attribute of the agents is the strategy they follow and our extension of the model. Most evacuation models assume all people have global knowledge of the exit location. However, evacuees tend to behave differently at the time of emergency and/or have different levels of knowledge about the environment. Therefore, they might adopt different escaping strategies. To describe the various evacuation planning of the agents, in this study we propose three types of strategies: *'nearest exit'*, *'hesitator'* and *'follow the leader'*.

The agents with strategy *'nearest exit'* are well aware of the location of the nearest exit, which defines their desired direction of movement. This strategy represents the case where agents have received safety instructions before accidents. They are assumed to only consider going through the nearest exit during evacuation, regardless of how crowded it is around the exit. Next, the agents with the *'hesitator'* strategy are easily influenced by the movement of their neighbors. At each time step, they have a 50% chance to follow the direction of their neighborhood and 50% chance to move towards the nearest exit. When the exit is in their vision range, they always adopt the *'nearest exit'* strategy. Distinct from the individualistic behaviors by *'nearest exit'* agents, the *'hesitator'* agents show herding behavior in evacuation. In real life, this behavior can be seen when evacuees are escaping from a smoky room where the exit is less visible, or when the evacuees have less confident planning of evacuation in an unfamiliar environment. The last strategy we experimented with is the 'follow the leader' strategy. The agent follows the first person it sees with a 'nearest exit' strategy. When they do not immediately see a neighbour with a nearest exit strategy, they keep looking until their vision is expanded three times. The first person they see with a nearest exit strategy is for that round their 'leader'. They walk in the direction to the previous location of the leader, essentially wanting to walk behind the leader. Just like with the 'hesitator' strategy they change to the 'nearest exit' strategy when the exit is visible , as they know the location of the exit.

Space is a very important factor in our model. We initialise all our agents in a continuous space. How close they are to each other or the wall influences how they react. Most importantly, they act according to local interaction. Agents outside their vision do not affect their behaviour.

Time in our model is measured in seconds, where each time step represents 0.01 s. Time in our model is thus discrete. However, as the time step is very small, it closely resembles the real life system, which has continuous time. Space is measured in meters, and by default a room of 15 by 15 meter is used.

2.1.3 Process Overview and Scheduling

In our model each entity moves through the room towards the exit incorporating where other people and obstacles are. Once the exit is reached, they are removed from the system. We used random activation as our scheduling method, in which every time step the new position of each agent is computed one by one, in a random order.

2.2 Design Concepts

2.2.1 Theoretical Background: The Social Force Model for Panicking Pedestrians

The actions of agents are mostly governed by forces modelling their behaviour. Such forces guide the agent towards their desired destination, and away from obstacles and other agents in their direct surroundings. The following discussion on forces is largely based on (Helbing et al., 2002). The agents are updated according to the differential equations $\mathrm{d}v_i/\mathrm{d}t = f_i(t)/m_i$ and $\mathrm{d}x_i/\mathrm{d}t = v_i$, where $f_i(t)$ denotes the sum of the forces acting on agent i. These are solved using the forward Euler method with step size $\Delta t = 0.01s$.

Acceleration force Every agent wants to move towards some destination — an exit, or any other point in space — which is modelled as a force in equation 1, with v_i^0 the desired speed, e_i^0 the desired (unit) direction, and v_i the current velocity of agent i. The acceleration force corrects the velocity towards the desired direction (at the desired movement speed), over a period of τ seconds.

$$f_i^{\mathrm{acc}} = m_i(v_i^0(t)e_i^0(t) - v_i(t))/\tau \tag{1}$$

Social force Agents tend to avoid each other, which is modelled by equation 2, where d_{ij} is the distance between agent i and j, the vector $n_{ij} := (n_i - n_j)/d_{ij}$ and $\cos\phi_{ij} = -n_{ij} \cdot e_i$. The parameters A_s and B_s are described in Table 1. Note that ϕ_{ij} is the angle between the desired direction of the agent and the direction of the force, and is used to influence the importance of the agent's field of view. The magnitude of the force decreases exponentially with distance.

$$f_{ij}^{\mathrm{soc}} = A_s \exp((r_i + r_j - d_{ij})/B_s) n_{ij} \left(\lambda_i + (1 - \lambda_i)\frac{1 + \cos(\phi_{ij})}{2}\right). \tag{2}$$

Obstacle force Obstacles in the simulated space cannot be passed through by agents, and must be avoided. This effect is modelled by equation 3, where d_{ib} is the distance between the agent and the obstacle, and $t_{ib} := (-n_{ij}^2, n_{ij}^1)$ is a (unit) vector tangential to the object. The parameters A_o and B_o are described in Table 1. The function $\Theta(z)$ is defined to be z if $z > 0$, and 0 otherwise. Essentially, the component containing the factor $\Theta(r_i - d_{ib})$ is only taken into account if the agent makes physical contact with the obstacle. Like the social force, the magnitude of the force decreases exponentially with distance.

$$f_{ib}^{\mathrm{obs}} = A_o \exp((r_i - d_{ib})/B_o) + k\Theta(r_i - d_{ib}))n_{ib} - \kappa\Theta(r_i - d_{ib})(v_i \cdot t_{ib})t_{ib} \tag{3}$$

Physical force If an agent makes physical contact with another agent, a physical force is applied, consisting of a 'body force' pushing the agent away and a 'sliding friction force' tangential to the body force. Again, the function Θ ensures that the component only takes effect if the agents make physical contact.

$$f_{ij}^{\mathrm{ph}} = k\Theta(r_i + r_j - d_{ij})n_{ij} + \kappa\Theta(r_{ij} - d_{ij})((v_j - v_i) \cdot t_{ij})t_{ij} \tag{4}$$

Panic level The *panic level* of an agent is determined by the agent's previous behaviour. It compares the average speed towards the desired destination of an agent with its desired speed as $n_i = 1 - \bar{v}_i/v_i^0$. Here $\bar{v}_i$ is the average of $v_i(t) \cdot e_i(t)$ over all time steps, and v_i^0 is the initial desired speed given to the agent at initialisation. The panic level influences the desired speed of an agent $v_i^0(t)$ as $v_i^0(t) = (1 - n_i(t)v_i^0 + n_i(t)v_i^{\max}$. Essentially, the agent tries to move faster if they have made relatively little progress towards their goal.

Environment Parameters			
Symbol	**Value**	**Units**	**Description**
N	100	-	Number of agents
w	1	m	Door size
-	15	m	Width building
-	15	m	Height building
Agent Parameters			
Symbol	**Value**	**Units**	**Description**
A_s	2×10^3	N	Intensity of social repulsion
A_o	5×10^3	N	Intensity of obstacle repulsion
B_s, B_o	0.08	m	Scale: controls how fast forces enlarges as agents move closer to each other
k_n	1.2×10^5	Kgs^{-2}	Stiffness coefficient
k_t	2.4×10^5	Kg	Friction coefficient
V	1	m	Vision
v_i^0	2	m/s	Initial desired speed
v_i^{max}	5	m/s	Maximum speed
$e_i^0(t)$	-	-	Desired direction at time t
τ (s)	0.5	s	Relaxation time
m_i	$50 - 80$	kg	Mass
λ	$0.7 - 0.95$	-	Reliance on what is in front
r_i	$0.37 - 0.55$	m	Radius
S	nearest exit	-	Strategy

Table 1: Parameter descriptions, symbols and theoretical bounds. These are the default values, in experiments these values may differ.

2.2.2 Model Parameters

2.2.3 Individual Decision Making

In the social force model at emergency evacuation condition, the decision of an individual agent at each step is driven by his desires and his interactions with any other agents and obstacles within the neighborhood. Referring to the descriptions by Helbing et al. (2002), during evacuation, the agent's desired velocity contains two components, the direction and speed. The desired direction of agents depends on current location of the agent and his strategy, as previously described in Section 2.1.2. The desired speed is scaled by the agent's panic level, see Section 2.2.1. Considering the desired velocity, the agent attempts to actively adjust his velocity following equation (1), summarized as the acceleration force. Meanwhile, the agent also takes each agent within the neighborhood into account for social effects. And the neighborhood of an individual is defined as the circle area with his vision as radius centered at his location. The social force applied to the individual is estimated by the social repulsive effect (equation (2)). And the physical force (equation (4)) is added if the two agents are crashing into each other. For each obstacle in the environment, the obstacle force effect onto the individual is calculated by equation (3). Lastly, the agent's velocity is updated as the joint result of acceleration force, social forces and obstacle forces, and his location is updated by $v_i^t \times \Delta t$. Note that, the individual speed should not exceed his maximum speed.

The activity flowchart in Figure 1 visualizes the updates of agent for each step during the evacuation. We also want to note that our model doesn't include any learning and prediction behaviors of agents. Because for emergent evacuations, it is rational to assume agents do not evolve their decision or predict the others behavior in such short period of time.

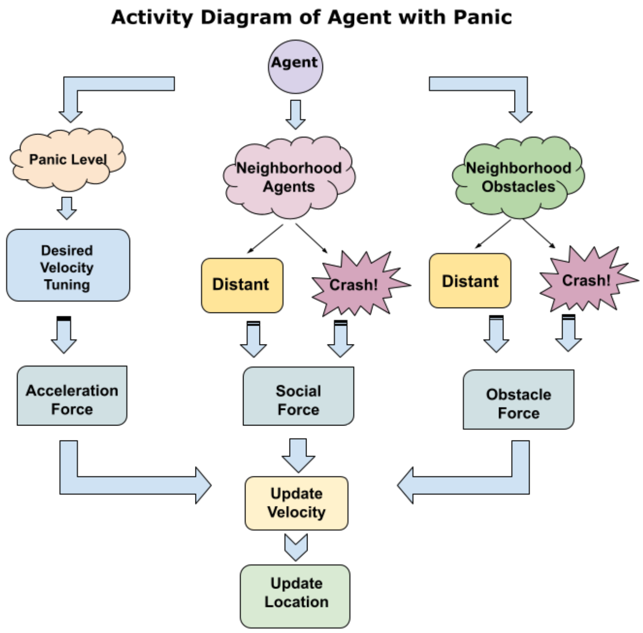


Figure 1: The individual decision making and status updating diagram for agents

Individual Sensing Having mentioned earlier, agents are able to sense different panic levels, depending on their relative evacuating rate on the desired direction. Agents are assumed to be able to detect any other agents within their vision distance. And by equation (2), we model the neighbors showing in front of the an agent has more social repulsive influence compared to the neighbors behind him. Since the only obstacles in the models are walls, we assume the agents are fully aware of their existence regardless of distance. But the repulsive force is slight when there is adequate distance in-between, which is easily interpreted from equation (3). Besides of the repulsive sensing, we also model the crashing sensing in terms of 'body force' and 'sliding friction force', when the distance between the mass center of an agent to another object is less than his shoulder width. In our model, the area taken by an agent is simplified as a circle with the shoulder width as diameter regardless of the direction he is facing. Nevertheless, the desired velocity of agent with *'hesitator'* and *'follow the lead'* strategies rely their decisions by actively sensing the movements of other agents in the neighborhood.

Interaction Following from the discussion of agent sensing procedure in Section 2.2.3, agents directly interact with each other by taking into account the repulsive and possible physical force to the update of their velocity. And the agents indirectly interact with their neighbors by taking their movements into decision process, when their strategy is *'hesitator'* or *'follow the lead'*.

2.2.4 Heterogeneity

At the initialization step, we create agents with part of their properties randomly drawn from uniform distributions on the corresponding ranges, see Section 2.1.2 and Table 1. Later for the extension experiments, we also randomly assign a strategy to agents with certain probabilities. So the agents are created heterogeneously, and they might be heterogeneous in decision making depending on their strategy.

2.2.5 Stochasticity

Aside from the random agent properties assignment we discuss in the previous section 2.2.4 at the initialization step, agents are also initialized at a random location in the room with a random initial velocity. Additionally, there is an equal chance of adopting *'following the neighborhood'* action or *'nearest exit'* action at each time step for the agents with *'hesitator'* strategy.

2.2.6 Observation

For our observation we looked at pedestrian flow, evacuation time and the percentage of agents that have been evacuated within the maximum amount of steps. The maximum amount of time is 100 seconds in most cases (10,000 steps) except during validation, where it is 1000 seconds (100,000 steps). The pedestrian flow is the time between agents exiting the building. It is defined by (Capelle, 2018) as

$$J = \frac{N-1}{t_N - t_1},$$

where N is the population size, t_1 the time in seconds when the first agents exits the room and t_N when the last person exits the room. If not everyone exits the room within the maximum amount of time, then N is the number of people that left the room and t_N the time when the last person within the maximum steps left. The evacuation time is the amount of time in seconds it takes for everyone to evacuate the building. The evacuation percentage shows the percentage of agents that got out within the maximum amount of time. In most cases this is 100%, but in some cases it is not. Then, the evacuation time is not determined, so it is interesting to look at the evacuation percentage.

3 Experimental Details

3.1 Initialisation

Upon initialisation, a room of 15 by 15 meters is constructed, and filled with agents at random positions. The agent parameters as described in Table 1 are drawn uniformly from the possible range.

In the experiment with varying strategies (Section 3.3.1), two cases are considered with a different initialisation. In the first case, agents are initialised with strategy 'nearest exit' with probability p, and with strategy 'follow the leader' with probability $1-p$. Secondly, agents are initialised with strategy 'nearest exit' with probability p, and strategy 'hesitator' with probability $1-p$. In other experiments, each agent has the 'nearest exit' strategy.

The environment is always initialised with walls at the border of the room, and a single exit. In the experiment with varying door sizes (Section 3.3.2), the size of this exit varies. In any other case, the size of the exit is set to a fixed size of 1 m.

3.2 Validation

There are several collective phenomena that can occur in the social force model (with panic), but a typical phenomenon is the arch-like blocking that occurs at the exit(s) (Helbing et al., 2002). This clogging at the exit leads to in-coordination between agents through which the efficiency of leaving the room is reduced. Due to time constraints and other limitations our model cannot be validated with real data. Thus, to validate our model we replicated the results by Helbing et al. (2002). We replicated the effect of desired velocity (or initial desired speed v_i^0 on the pedestrian flow J ($m^{-1}s^{-1}$) divided by the desired velocity. For this experiment, we disabled the panic level in agents and set the initial desired speed v_i^0 from 0.5 to 5 m/s with steps of 0.25 m/s. For our input parameters, we took the same values used in the same experiment in Helbing et al. (2002). These are our default parameters, except that the population size N was increased to 200 for this experiment. We repeated the experiments 10 times.

3.3 Extension Experiments Design

For the extension studies of this research, we focus on analyzing the effects to the evacuation performance by introducing different strategies into the population and varying the size of exit in the environment.

3.3.1 Different Strategies in the Population

The strategies people adopt can differ among agents. It can vary based on past experience, mental states and knowledge of the environment. Introduced in Section 2.1.2, we have designed and implemented 3 strategies, *'nearest exit'*, *'hesitator'*, and *'follow the leader'*. The *'nearest exit'* strategy is the default strategy. We are interested in the change of evacuation performance given different mixtures of strategies in our population. In this experiment, we focus on comparing only two different strategies existing in the population at the same time and vary the fractions with which these strategies are adopted. Particularly, we will compare the *'nearest exit'* against the *'hesitator'* and the *'nearest exit'* against the *'follow the leader'*.

3.3.2 Varying Exit Size in Environment

The relationship between exit location and evacuation efficiency has been widely studied in literature (Haghani & Sarvi, 2019). However, although the positive correlation between bigger exit size and shorter evacuation time is apparent, few studies has looked into the sufficient size of exit for good evacuation efficacy. Hence, we design this extension experiment to find out the sufficient size via simulations.

3.4 Sensitivity Analysis

Sensitivity analysis assists the understanding the relative importance of different input vectors on the simulation outcomes (Roy, 2022). Mentioned in Section 2.2.1, the social force model for panic emergency evacuation consists of 4 environment variables and 14 agent variables. The exact values of some agent parameters, such as intensity of social and obstacle repulsion (A_s and A_o), vision, and maximum speed (v_i^{max}), are difficult to be validated from the limited source of real life data (Sticco, Frank, & Dorso, 2021). Therefore, it is helpful to include sensitivity analysis for estimating the uncertainty of simulation outcomes, identifying important factors and testing the robustness of emergent properties (Roy, 2022).

Our sensitivity analysis is done in two parts, both based on the model with default parameter value setting introduced in 3.1. At the first part we perform a local sensitivity analysis utilizing the One-factor-at-a-time(OFAT) approach. OFAT reveals the effect of parameter by varying it along while fixing the others. In this research, parameters *population*(N), *relaxation time*(τ) and *door size*(W) are chosen to be analyzed by OFAT. The second part of sensitivity analysis focuses on the interaction effects between parameters by means of the Sobol method (Sobol, 2001), a global sensitivity analysis tool. By assuming all parameters are independent, Sobol approach measures the sensitivity of factors by estimating their contribution to the variance of outcome (Ten Broeke, Van Voorn, & Ligtenberg, 2016). To study the repulsive effect and its influence to the evacuation performance, we vary *intensity of social repulsion*(A_s), *intensity of social repulsion*(A_o), *vision*(V) and *maximum speed*(v_i^{max}) in Sobol analysis.

3.5 Implementation Details

The model is implemented in Python 3 in the Mesa framework for agent-based modelling[1]. Analysis is done using Python scripts and Jupyter notebooks (in Python). Any code used for the model, analysis, validation, and experiments is publicly accessible, including the resulting data[2]. The file `Readme.md` in the project[2] contains more information about the project structure, and instructions for running the code.

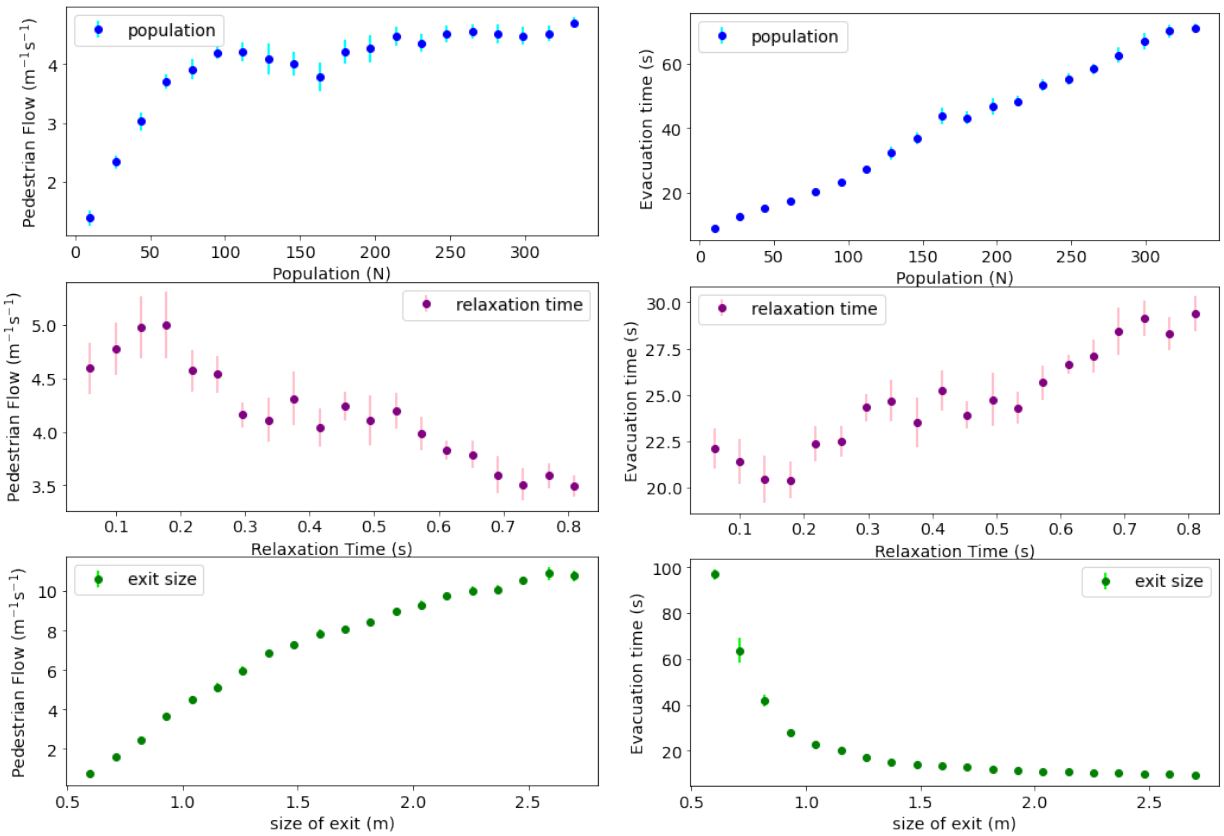
[1]https://github.com/projectmesa/mesa

[2]https://github.com/thijs-blom/agent-based-modelling

4 Results and Analysis

4.1 Sensitivity Analysis

For local sensitivity analysis we analyse the factors of interest with the OFAT approach as described in Section 3.4. The first input factor is *population*, which takes a value from 10 to 333. The population size of 333 is estimated to be the maximum capacity of a conference room with comfortable room for each person (Matthews, 1970). The second factor is *relaxation time*. The relaxation time is taken from 0.06 to 0.81 seconds, which covers the range of value measured from empirical cases in literature (Haghani & Sarvi, 2019; Johansson, Duives, Daamen, & Hoogendoorn, 2014). The last factor is *size of exit*, which varies from 0.6 to 2.7 meters. This range of value is based on the UK door size standard, which suggest a single leaf door to be around 0.61-0.91 meters, a double leaf door to be approximately 1.2-1.8 meters, and a big gate can be up to 2.7 meter (*What are the standard doorsize in your country?*, 2022).



(a) (b)

Figure 2: *Local sensitivity analysis for variables population, relaxation time, and size of exit with measurements pedestrian flow on plot (a) and evacuation time on plot (b). The error bars around the mean constitute the 95% confidence interval.*

For each factor, we generate 20 distinct samples, and repeat the simulation 10 times for each sample. Figure 2 shows the results using measurements *pedestrian flow* on subplot (a) and *evacuation time* on subplot (b). When the population size increases, the total evacuation time increases linearly, while the pedestrian flow remains at a rather stable value after the population size exceeds 100 agents. This means that, when the number of evacuees is bigger than 100, the jamming pattern around the exit starts to form. Next, we find there is a positive correlation between size of exit and evacuation performance. The pedestrian flow linearly goes up as the size getting bigger. The evacuation time drops exponentially, meaning that smaller door size have more negative impact on evacuation time but when the doorsize exceeds about 1.5 meters, evacuation time does not further decrease much. Lastly, as we increase the relaxation time, the pedestrian flow generally decreases and evacuation time increases. This is expected, since a larger relaxation time means a larger delay for agents to reach their desired velocity. We should note that the uncertainty of the OFAT results about the relaxation time factor is comparatively large, which might be explained by underlying interaction effects with other parameters. We suggest to apply global sensitivity analysis in the future for relaxation time.

For the global sensitivity analysis, we utilize the Sobol method. The first factor here is the *insensitivity of obstacle repulsion*, which is also denoted as *obs strength* in short. Its value is taken from 2000 to 5000 N. The second factor is *insensitivity of social repulsion*, or *soc strength* in short. Its value is taken from 1000 to 3000 N. The third factor is *vision*, which varies from 1 to 5 meters. The last factor is *maximum speed*. The maximum speed is approximated as the average running speed of an adult, which ranges from 3 to 5 m/s depending on gender and age.

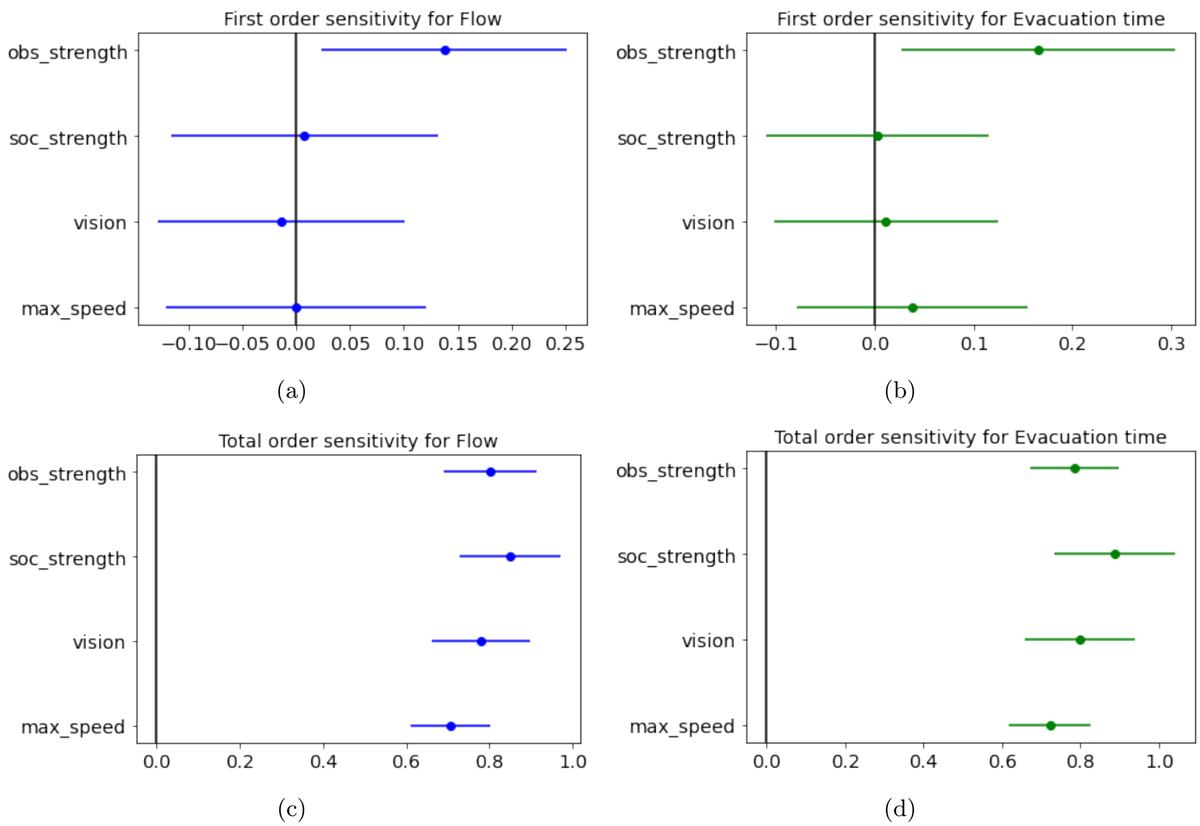


Figure 3: *Global sensitivity analysis for variables population, relaxation time, and size of exit with pedestrian flow and evacuation time as outcomes*

In our Sobol analysis, we sample 512 samples following the Saltelli's sampling scheme and analyze the first and final order indices given by Sobol approach. We perform 5 iterations for each samples and repeat the Sobol analysis for each iteration. Figure 3 presents the visualized result from one of the analyses using measurements pedestrian flow (subplot (a)) and evacuation time (subplot (b)), where the error bars suggest the uncertainty of the estimations. Looking at the first order sensitivity indices of both measurements, around 15% of the total variance is contributed by the *insensitivity of obstacle repulsion*, while the contributions is estimated to be around 0 for the other factors. However, the total order sensitivity indices are much higher for all factors. And the estimation for *insensitivity of obstacle repulsion* has the highest average value among all, valuing more than 85% by both measurements. These results suggest that there exit some higher-order interactions between the factors, which have more impacts to the variance than those factors along. The other 4 repetitions of our Sobol analysis provide similar results.

4.2 Validation

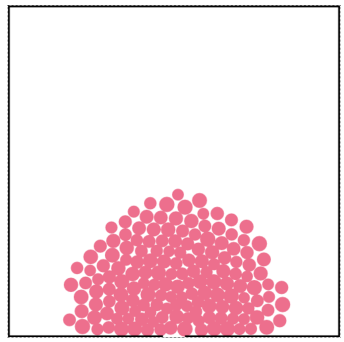
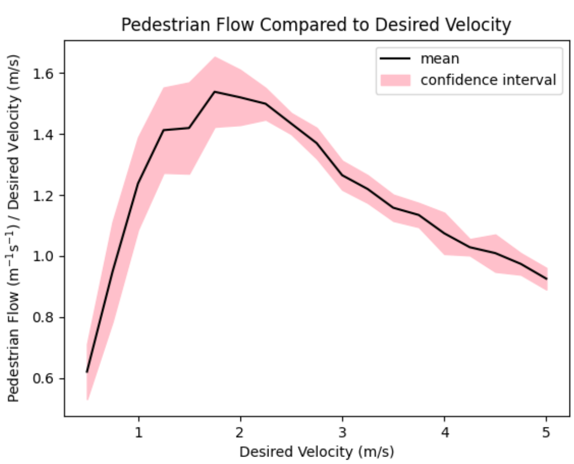


Figure 4: *Visualisation of the arch-like blocking for* $v_i^0 = 2.0$ *with disabled panic effect at* $t = 10$ *s.*

Firstly, we see a clear formation of an arch blocking around the exit (see Figure 4). Secondly, in the left plot of Figure 5 we can clearly see that initially the flow relative to the desired velocity is increasing. Thus, people are exiting faster after each other than the desired velocity increases. Yet, for desired velocities above 2 m/s the flow seems to decrease again. This means that although be people want to move faster, the flow is not increasing as fast as the desired velocity. This is also shown in the right subplot of Figure 5, where the evacuation time seems to exponentially decrease from v_i^0 0.5 to 2, but where-after further increases of the desired velocity barely decrease the total evacuation time. This result is similar to the results found by (Helbing et al., 2002), although flow is generally lower (with a peak at 1.2) and occurs already at a desired velocity of 1.5 m/s. Further, in their model the evacuation time actually increases of $v_i^0 = 1.5$ m/s. We must note, that the variance between v_i^0 1 and 2 m/s is larger than with the other velocities. There seems to be an effect where it sometimes takes a lot of time until the last few people exit the room. Future research should set out to explore the underlying reason for this phenomena, which could explain the slightly different results compared to (Helbing et al., 2002). Further, we did not include an attractive force between some people, while they did.



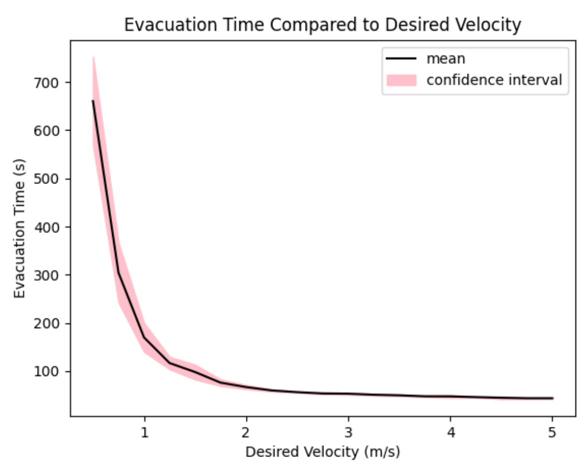
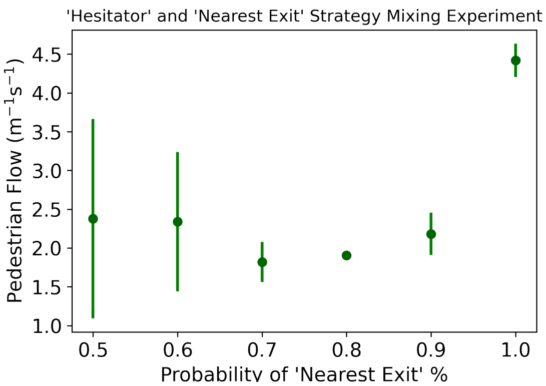


Figure 5: *The left plot is the computed mean over of the pedestrian flow divided by the desired velocity compared to the desired velocity. The right plot is the evacuation time compared to the desired velocity. Both plots result from 10 repetitions with intervals of 0.25 m/s in the desired velocity. The confidence interval is plotted around the mean.*

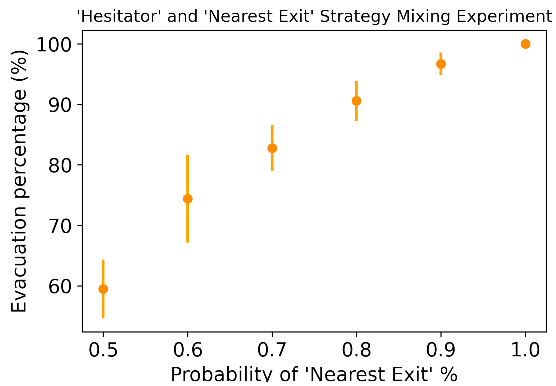
4.3 Extension Experiments

4.3.1 Different Strategy

We perform two strategy mixing experiments. In the first strategy mixing experiment, we increase the fraction of the population that has the *‘nearest exit’* strategy from 0.5 to 1.0 in steps of 0.1. The other fraction is the people that follow an *‘hesitator’* strategy. In the second strategy mixing experiment, we increase the fraction of the population that has the *‘nearest exit’* strategy from 0.1 to 1.0 in steps of 0.1. The other fraction is the people that follow an *‘follow the leader’* strategy. We set the maximum simulation time to be 100 seconds. We repeat the simulations for 5 times each. Again, we use the pedestrian flow and successful evacuation percentage by the end of simulation as the outcome variables.



(a)



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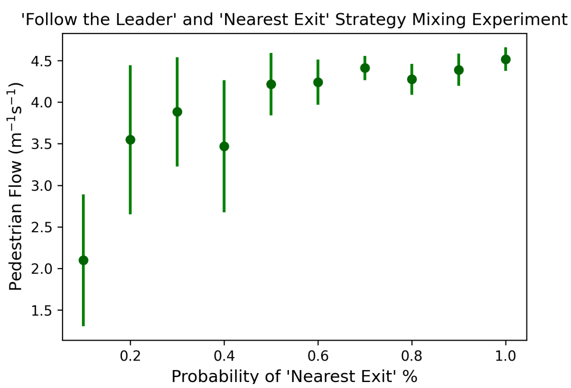
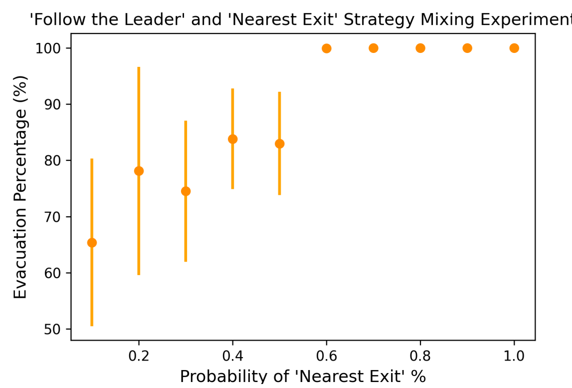


(c)



(d)

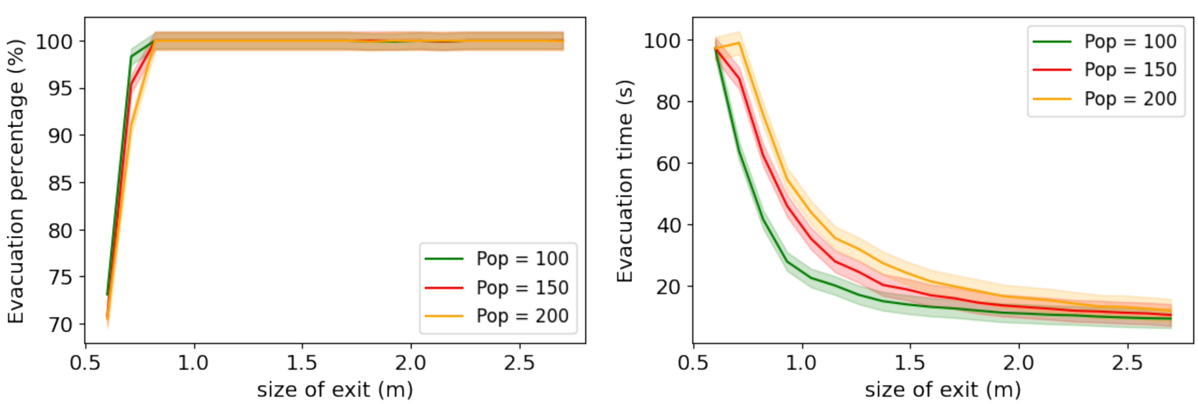
Figure 6: *The results of the experiments with strategy mixing. The top row mixes the ‘hesitator’ and ‘nearest exit’ strategies and are plot against pedestrian flow (a) and evacuation percentage (b) as outcome variables. The bottom row mixes the ‘follow the leader’ and the ‘nearest exit’ strategies against pedestrian flow (c) and evacuation percentage (b). The points are the mean values over 5 repetitions. The error bars represent the 95% confidence interval around the mean.*

Figure 6 visualizes the simulation results. In subplot (a) of Figure 6, we find that the pedestrian flow results becomes highly uncertain when the proportion of *‘hesitator’* agents increases. We can also see that value of the pedestrian flow goes up significantly when more than 90% of the population follows the *‘nearest exit’* strategy. In subplot (b), the rate of successful evacuation almost linearly increases as the proportion of *‘hesitator’* agents decreases and the confidence interval also shrinks. Also observing from the visualization of the strategy mixing model, we find that the *‘hesitator’* agents are not so rational. Sometimes they follow another hesitator and then together move away from the exit. Also we observe that, when there are push-backs going on near the crowded exit, the hesitators are affected and start moving backwards. This may avoid physical contacts but also decreases evacuation efficiency. These observations are in line with our discussions from the statistical simulation outcomes. Our results suggest that the 'herding behavior' exhibited by the agents with a *'hesitator'* strategy leads to poor evacuation performance, which is confirmed by the findings from the empirical cases studies (Coleman, 1994), (Johnson, 1987), and (Elliott & Smith, 1993).

Subplot (c) and (d) show the effect of different proportions of agents with a *'follow the leader'* and *'nearest exit'* strategy. The main trend is the same as with the *'hesitator'* strategy experiment, but the the flow increases already at a 50-50 split within the population. However, the best flow with the least variance is still when everyone follows the *'nearest exit'* strategy. What is most important is that when the population consists of less than 60% agents with a *'nearest exit'* strategy, often not everyone gets out within 100 s, yet after this everyone always gets out. Thus, after about a 60%-40% distribution with a majority having the *'nearest exit'* strategy, the evacuation performance is similar to that when all agents follow the *'nearest exit'* strategy. This makes the *'follow the leader'* strategy seem better than the *'hesitator'* strategy. An explanation of this could be found when looking at the emerging behaviour in the model. As you can see in Appendix Figure 8, there sometimes seems to been a line following a leader (subplots c and d on the right). Yet, what also can occur is that they come into a deadlock, where they do not move anymore, see the emerging cluster in the top left, this can result in not everyone getting out. Most of the population however still clogs at the exit. When the formation breaks, the agents with a *'follow the leader'* strategy leave the exit more than the *'nearest exit'* strategy agents. For further research, different implementations of the *'follow the leader'* strategy could be tried and evaluated.

4.3.2 Varying Exit Size

In this extension experiment, we explore the critical value of exit size by varying the value from 0.6 - 2.7 meters, utilizing the default model setting (see Section 3.1) with population equaling to 100, 150 and 200. We use 20 discrete uniformly sampled values in the range of exit size, and 10 repetitions of simulations.



(a) (b)

Figure 7: *Experiment with varying size of exit from 0.6 to 2.7 meters, evacuation performance are measured with outcome variables (a) evacuation percentage and (b) evacuation time*

The results are shown in Figure 7, where the filled area around the lines in each plot denotes the confidence interval and the lines denote the average value. As what we expected, evacuation with larger population is more challenging and takes more time for everyone to escape. In subplot (a), the successful evacuation rate starts at around 70 - 73 % when the exit size is 0.6 meter. Then it significantly increases to 100% when the size of exit reaches around 0.82 - 0.92 meters, which is the threshold to allow more than half of any two randomly selected agent to pass the same time. By analyzing the evacuation time in subplot (b), we also find the improvement slows down significantly after reaching the threshold for all three cases with different number of initialized population. And the evacuation time becomes stable if the size of exit is larger than 2 meters. Thus, our experiment suggests size of exit should allow two people to pass the same time for better evacuation efficiency.

5 Conclusion

In short, we created an ABM version of the social force model extending it with a panic effect and different strategies. We looked into how changing certain parameters in the model influence the model outcome, measured in evacuation time (or percentage) and pedestrian flow. We found that the *'nearest exit'* strategy performs best, but assumes global knowledge, which is not always realistic. We also found that the door size of the exit should be as least as big as two agents, as this will significantly lead to better evacuation performance. We also found a positive effect of population and relaxation time on the evacuation time. Thus, bigger populations and a longer relaxation time leading to longer evacuation times. In our global sensitivity analysis we saw that the total effect of of each parameter was large and thus all factor are important. In future research we would like to expand the model further with injuries and casualties and it could be applied to specific scenarios and environments.

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Appendix

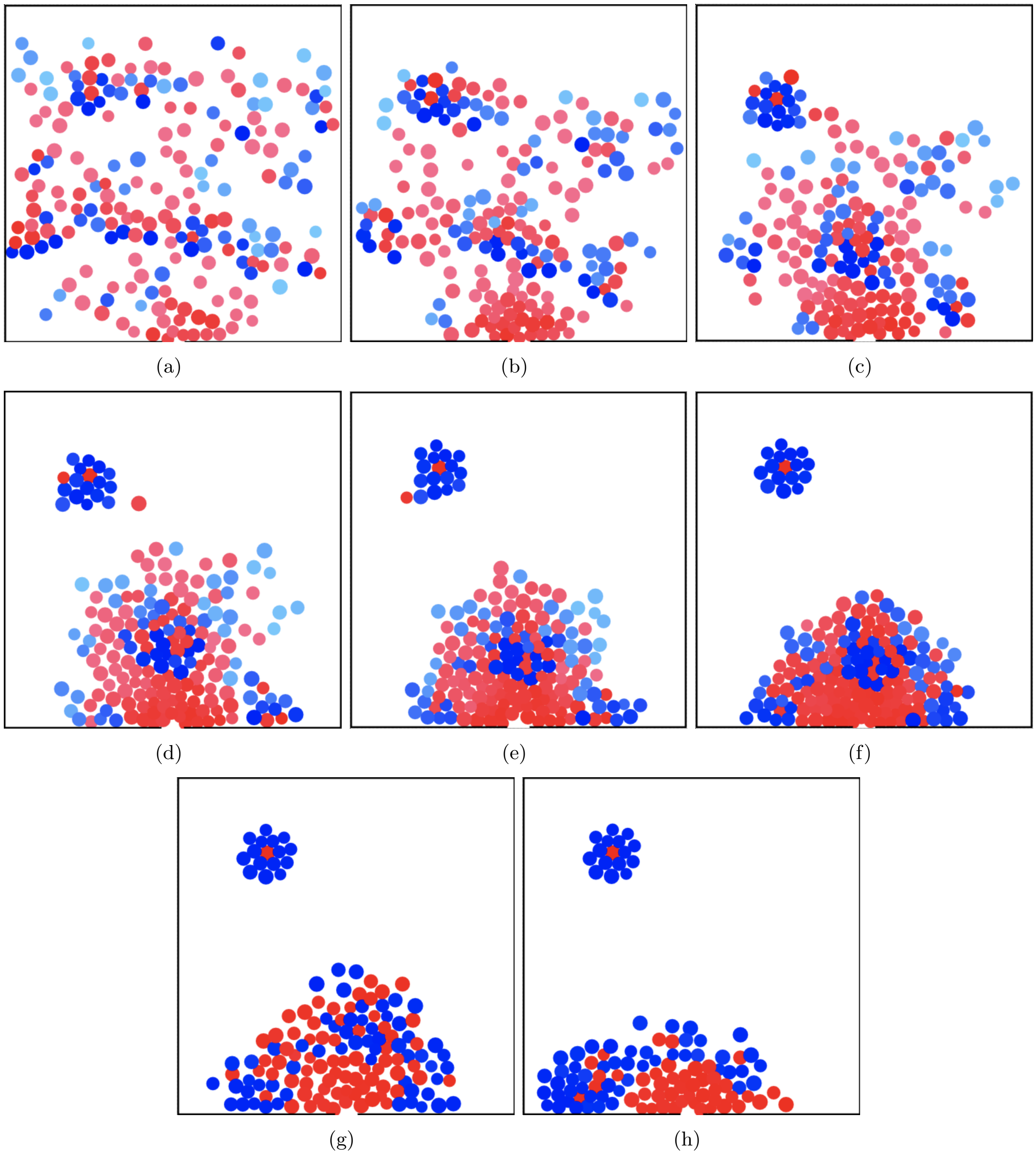

Figure 8: *Simulation of mixed strategy population, where 40% follows the 'follow the leader' strategy (blue) and 60% the 'nearest exit strategy' (red). The different sub-figures are taken from (a) 1 second, (b) 2 seconds, (c) 3 seconds, (d) 4 seconds, (e) 5 seconds, (f) 7 seconds, (g) 14.5 seconds and (h) 22 seconds. The brighter the color, the more panicked they are.*