

# Influence of Human Behaviour in the Evacuation of a Burning Building

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## 1 Abstract

Within the last decade, an increasing focus has been put into simulating evacuation procedures [4]. These simulations often cover topics such as herding behaviour, leadership hierarchy distribution and general game theory. During this research project, we propose a study focusing on the behaviour of self-preservation versus collective assistance as arisen by recent observations of emergency evacuations [2], when agents are presented with a spreading danger such as a fire. The success metric of our model will therefore be based on the percentage of people (agents) that successfully escaped, when comparing different levels of agent collaboration.

## 2 Introduction

This paper is investigating the evacuation success (percentage agents escaped), whilst varying the level of collaboration between agents. The main hypothesis has been formed as follows; there is a positive correlation between the percentage of collaborating agents and evacuation success (percentage agents escaped). Which can be formed into the following research question: Does agent collaboration improve the success of an evacuation, compared to self-preservation tactics?

As there has been no similar research for comparison purposes, two simulation models have been developed to test the hypothesis. The first is implemented in NetLogo and depicts basic human behaviour, abstracting realistic environmental elements. The second is implemented using a Python agent-based modelling framework (Mesa link), which expands the algorithms realized in NetLogo with more sophisticated heuristics. To obtain the results, the models have been run copious times with comparable parameters, thus leading to homogeneous statistical results for the purpose of placing the outcomes of each model side by side. The results obtained from the two models are conflicting in regards to the hypothesis.

For each of the implementations, the paper follows the subsequent structure;

1. defining the parameters used, their characteristics and the heuristics applied, 2. describing the experimental setup and 3. presenting the results. Next, the conclusions section depicts the expected outcomes in juxtaposition to the results of the two models and their comparison. Finally, the paper concludes with a discussion about future work suggestions and extensions of the sophisticated (Mesa) model.

## **3 Netlogo Model**

### **3.1 Model Design**

The first model has been created with NetLogo, a multi-agent programmable modelling environment and does not utilize any of the pre-existing models in the NetLogo library. This model is an abstraction of rules occurring in the real world. The environment is 33x33 grid of patches representing a floor plan. The agents consist of fire agents and different types of human agents.

#### **3.1.1 Floor Plan**

The floor plan consists of four equal sized rooms with one exit each, leading to a corridor with one main exit (Figure 1).

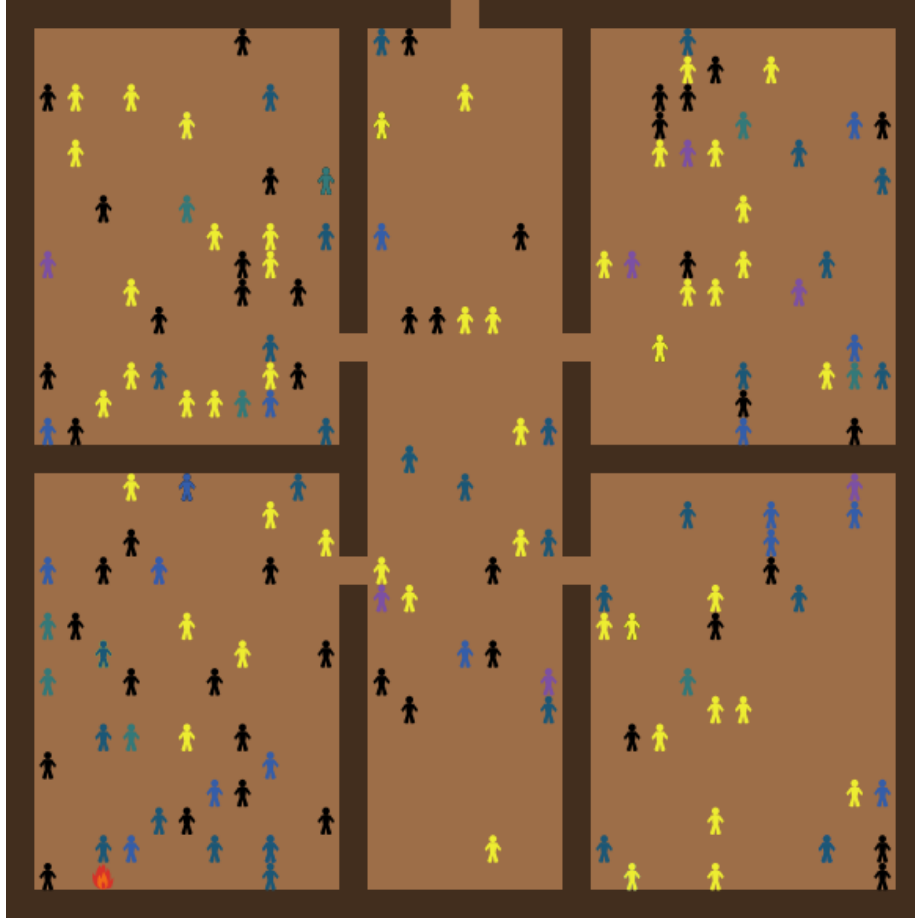


Figure 1: Example of the view of the model as it is first setup.

### 3.1.2 Human Agents

Human agents are divided into helpers (humans that do not affect the movement of other humans) and non-helpers (humans that affect the movement of other humans).

The different types of non-helpers are:

- People-evacuating  
Agents that acknowledge the alarm and are searching and moving towards the exits.
- People-panicking  
People that acknowledge the alarm and move rapidly and randomly.
- People-ignoring-the-alarm

People that do not acknowledge the fire alarm and remain stationary, unless there is fire or smoke in their vision, in which case they turn into people-panicking.

The different types of helpers are:

- Flocking-helpers  
Helpers that form groups with stationary and panicking people and move towards the exit.
- Vocal-helpers  
Helpers that shout out the location of an exit when it is within their vision.
- Strong-helpers  
More physically capable, this type of helpers move towards people with diminished health and carry them towards the exit.
- Kangaroos  
Kangaroos are agents formed by the conjoining of a strong helper and another type of human agent.

Table 1: Human Agent Attributes

Attribute	Data Type / Range	Description
Health	Unsigned Integer (0 to 50)  Unsigned integer (0 to 80) for strong-helpers	Represents the health of the agent. Zero being dead, 30 (80 for strong-helpers) being perfectly healthy and any decimal values in-between representing severity of health condition.
Speed	Decimal (0 to 1)	When the value is 1 the position of the agent is renewed per time frame. The frequency of position updates decreases as this number decreases. Speed is set at 0.3 when $20 \leq health < 30$ and at 0.1 when $health < 20$
Shout (only for vocal-helpers)	String	The shout is initialized at an empty string "". When an exit is in radius 2 of the agents current position, the value of the shout becomes "exit is here".

### 3.1.3 Fire agents

The fire is represented as a cellular automaton, spreading by checking the existence of smoke in neighboring tiles.

## 3.2 Algorithm description

Initialize the model:

1. Setup floor plan.
2. Setup the amount of the different types of human agents according to user input.
3. Setup a fire agent at a random tile.

For each time step do:

1. Check health  
Every time an agent is on a tile with the color "grey", which indicates the presence of smoke, the health of the agent is reduced by 1.
2. Check death  
Health of a human agent is 0, which can happen by either crossing a fire tile, either health being diminished by the smoke.
3. Move human agents  
Basic movement: Move one patch ahead per time frame at a speed determined by health status towards the direction faced at previous time step. When the main corridor exit is in view (2 patches ahead), move towards the exit, pass through, increase the people-escaped and type of people-escaped accordingly.
  - 3.1. People-evacuating  
Follow basic movement. When a wall or a patch with fire is encountered, make a random turn. When there is a vocal helper whose shout attribute has the value "exit is here", turn to face and move towards the exit, therefore extend vision by two.
  - 3.2. People-panicking  
Move randomly, ignoring the presence of exits. Do not avoid fire. When flocking helpers exist in any of the patches in radius two, turn to face the flocking-helper minimum distance and follow. If the distance between the flocking-helper and the people panicking increases to a number larger than five patches, the panicking agent stops following the flocking agent and returns to a state of panic.
  - 3.3. People-ignoring-alarm  
Stationary. When there is a flocking-helper in radius two, follow the same heuristic as people panicking. When there is a fire in radius two of their current position, convert into people-panicking.
  - 3.4. Flocking-helpers  
Basic movement.
  - 3.5. Vocal-helpers  
Basic movement. "Shout" the position of an exit when it is visible in radius 2 of current position.

### 3.6. Strong-helpers

Basic movement. When there is a person-evacuating with health lower than thirty in radius three, move towards the agent until they arrive at the same position, at which point a kangaroo is formed.

### 3.7. Kangaroos

Basic movement.

## 4. Spread fire and smoke

A new smoke-tile is created per time frame when at least one of its neighbours is a smoke tile. A new fire-agent is sprouted when at least one neighbor is a fire-agent and the rest of the neighbors are smoke tiles.

## 3.3 Experimental Setup

The BehaviorSpace tool of NetLogo is used to conduct the experiment. The variables varied during the runs are the different types of humans. Non-helpers can take the values “50” or “100”. Helpers are assigned the values of “0”, “50” or “100”, to measure their influence into the success of the overall amount of people escaped and the amount of non-helpers escaped. The experiment is set to return the total amount of people escaped and the amount of non-helpers escaped. The stop condition for each run is when the total amount of people has either escaped or died.

The model is run with all the different types of combinations of the number of humans aforementioned and repeats each combination eleven times, yielding a total number “2,376” runs.

## 3.4 Results

The results of the experiment have been exported and contain the following data for each run:

- The amount of humans of each category
- The amount of humans escaped
- The amount of non-helpers escaped

For each run, the percentage of helper agents and the percentage of all the human agents escaped has been calculated. The percentage of non-helpers escaped in relation to the total amount of non-helpers per run has also been calculated. The data has then been reordered according to the percentage of helpers. For each of the different percentages two different boxplots have been generated; one for the percentage of the total people escaped and one for the percentage of the non-helpers escaped, in order to find and eliminate outliers. Figure 2 depicts an example of a boxplot obtained.

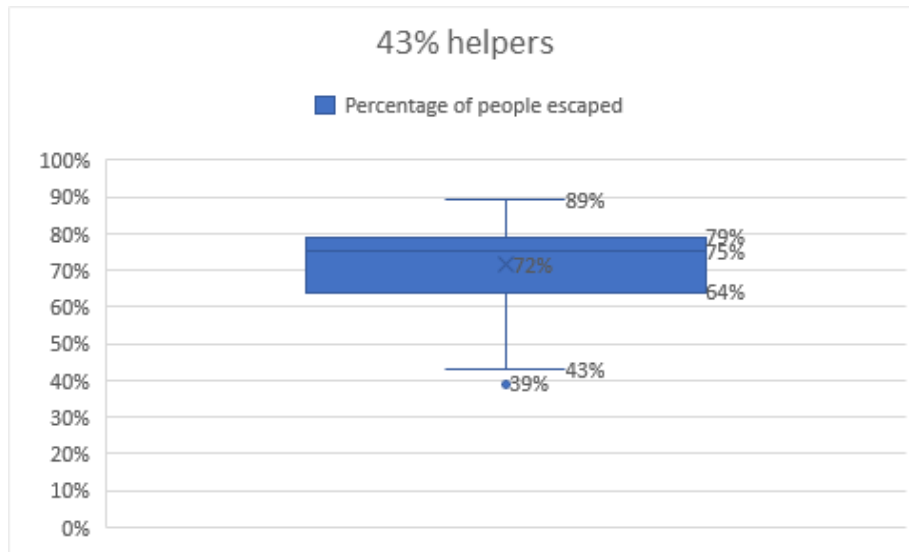


Figure 2: Example of a boxplot showing the success of people evacuating for a percentage of helpers at 45%.

Subsequently, a number of graphs has been generated to observe the influence of the existence of helper agents to the escape success. It is noted that the overall escape success for each percentage of helpers is increasing as the number of helpers increases (Figure 3). The same applies to the graph generated where the success of escape for the non-helpers is reported (Figure 4). However, it can be noted that there is a slight decrease when the amount of helpers makes up the 50%-60% of the total number of humans, as well as above the 60%.

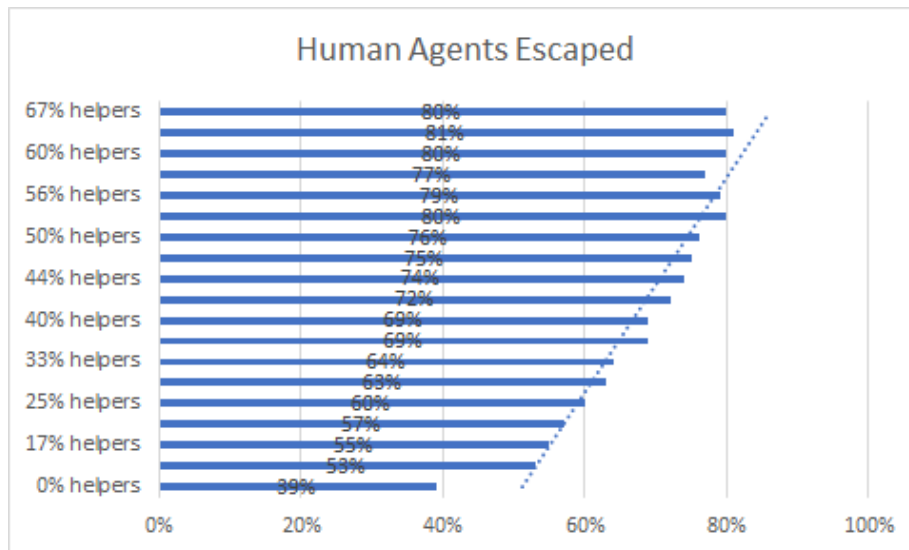


Figure 3: Bar chart showing the average percentage of agents escaped, over different percentages of helpers.

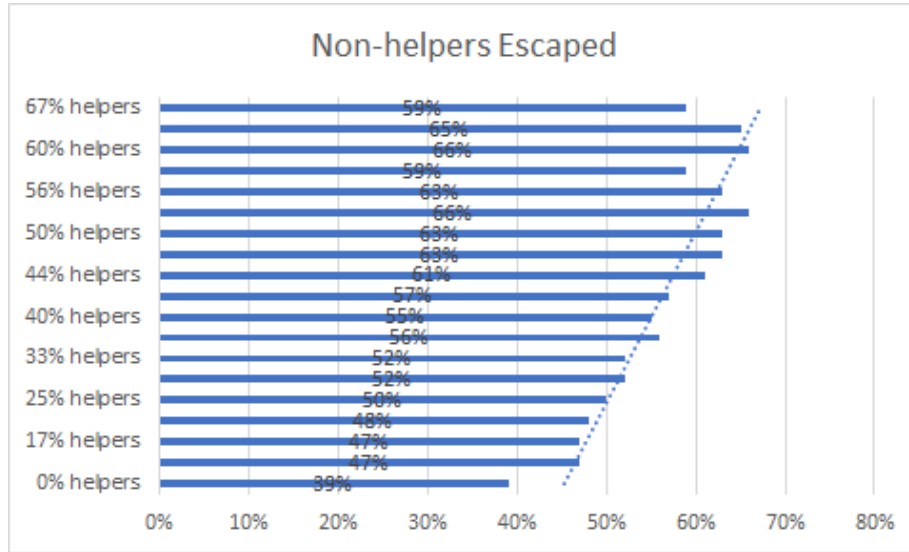


Figure 4: Bar chart showing the average percentage of non-helpers escaped, over different percentages of helpers.

A graph illustrating the influence of different types of helpers in the escape success of non-helpers (Figure 5), shows that the most positive influence in escape success is a result of the presence of flocking helpers. This is evident as we look at the escape success of non-helpers for a percentage of flocking-helpers at 100% out of the total amount of helpers. When all of the helpers are either vocal helpers or strong helpers, almost identical results can be seen.

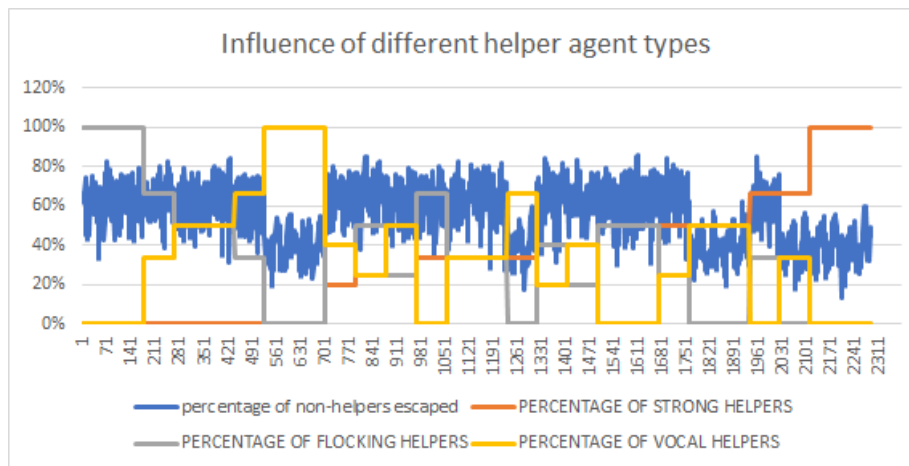




Figure 5: Line graph showing the effect that the percentage of each type of helper has on the success of non-helpers escaping.

## 4 Advanced Model

The advanced model has been developed using Project Mesa, a Python based ABM (agent-based modelling) framework. Utilising a diverse language such as Python allowed us to create complex heuristics which would not have been possible in Netlogo.

### 4.1 Model Design

#### 4.1.1 Floor Plan

The layout that will be used and focused on for the rest of this paper, is one which attempts to replicate the floor-plan of the NetLogo model, so that we could achieve accurate comparisons. The difference between the floor plans of the two models is that the Mesa model contains interactive objects.

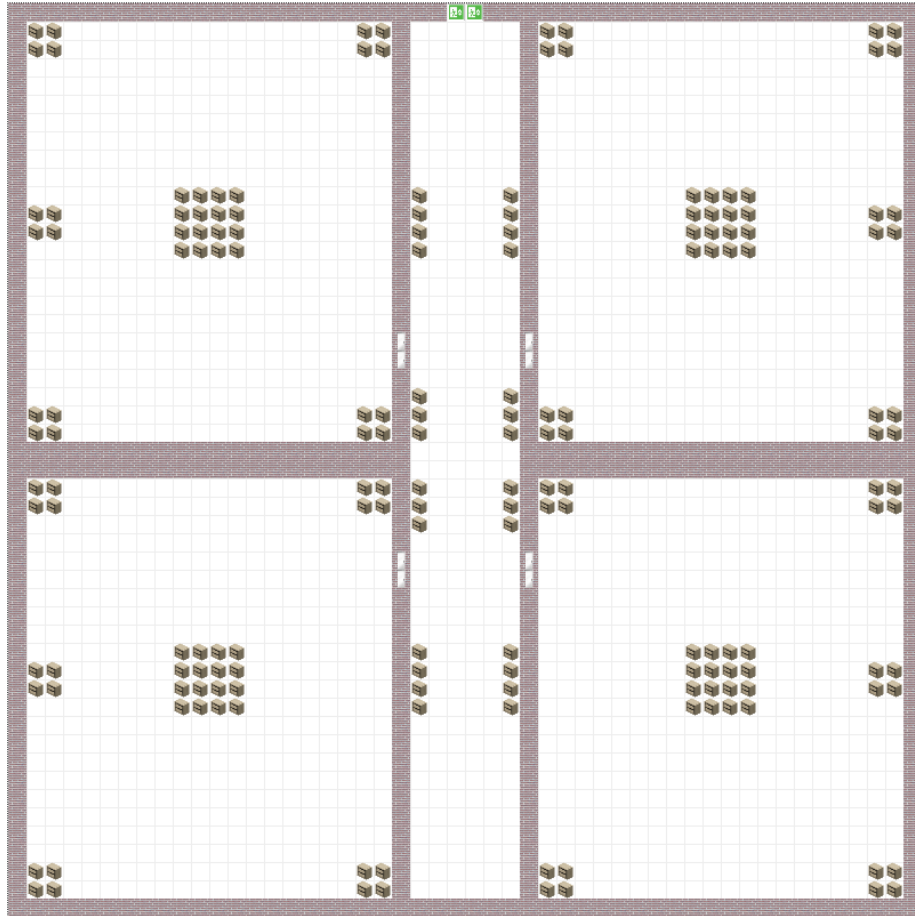


Figure 6: The tested floor-plan

All agents and objects use the attributes specified below.

Table 2: Floor Object Attributes

Attribute	Data Type / Range	Description
Flammable	Boolean	Indicates whether fire can spread to the given floor object. If false, fire will not replicate on this tile. Only Human agents and furniture are flammable.
Visibility	Unsigned Integer (0 to n)	Represents how easily seen an object is, through the smoke of a fire.
Traversable	Boolean	If an object can be moved over, this value is true.

#### 4.1.2 Human Agents

The majority of attributes below take influence from those proposed by Emilio, Rosaldo et al. [1].

Table 3: Human Agent Attributes

Attribute	Data Type / Range	Description
Position	Coordinate (X,Y)	The coordinate of the agent’s current location.
Health	Decimal (0 to 1)	Represents the health of the agent. Zero being dead, one being perfectly healthy and any decimal values in-between representing severity of health condition.
Mobility	Unsigned Integer (0 to 2)	A value to represent the current mobility state of an agent. Zero indicates that they can not move, 1 indicates normal movement and 2 indicates panic movement.
Speed	Unsigned Integer (0 to 2)	The number of tiles the agent can move per step.
Vision	Unsigned Integer (1 to Floor-plan size)	The range value of an extended Moore neighbourhood, where the agent is the center point. Smoke has an impact on vision, according to previous research on visibility in fire smoke [2].
Visibility	Unsigned Integer (1 to n)	The visibility of the agent when determining if the agent is visible from a given location, possibly through smoke.

Collaborates	Boolean	A value denoting whether or not an agent is willing to collaborate with other agents.
Collaboration Count	Integer (0 to n)	A value keeping count of how many successful collaborations the agent has made. As this value rises, the probability that the agent will help again decreases exponentially.
Knowledge	Percentage	A percentage representing the agent's knowledge of their environment.
Nervousness	Unsigned Integer (1 to 10)	Represents the agent's mental stability. This value influences how they behave when confronted with various scenarios.
Shock	Decimal (0 to 1)	If the agent sees something which shocks them, this value increments accordingly and is used when deducing if the agent will enter panic mobility.
Experience	Unsigned Integer (1 to 10)	Represents the agent's previous experience with emergency situations, with zero representing no experience and 10 representing the highest level of experience. Experience influences how the agent can help others and also their threshold to panic.
Believes Alarm	Boolean	Indicates whether or not, the agent will believe the fire is real when it first starts. This will change to true if they are verbally collaborated with, or they see the fire/smoke.

#### 4.1.3 Fire Agents

The fire is a Cellular Automaton. Its implementation is influenced from that described by Tissera, Castro, Printista and Luque [5].

Table 4: Fire Attributes

Attribute	Data Type / Range	Description
Smoke Radius	Unsigned Integer (1 to n)	The range value of an extended Moore neighbourhood, where the fire is the center point.
Smoke Spread Rate	Unsigned Integer (1 to n)	The number of model steps it takes for the smoke to spread into its Moore neighborhood.

## 4.2 Algorithm Description

For each time step that the agent is alive and hasn't escaped:

1. Check Health/Mobility
  - 1.1. For each fire tile within the agent's neighborhood, reduce the agent's health value by 0.2 and their speed value by 2.
  - 1.2. For each smoke tile within the agent's neighborhood, reduce the agent's health value by 0.1 and their speed value by 1.
  - 1.3. If the agent's speed reaches zero, set their mobility to zero.
  - 1.4. If the agent's health reaches zero, set their mobility to zero and mark them as dead.
2. Update the agent's vision with the currently visible objects/tiles.
3. Check state of panic:
  - 3.1. Calculate the shock value of the agent according to occurrences of smoke, fire, panicking agents or dead agents in their vision. If there are none, decrease their shock value.
  - 3.2. Calculate  $score_{\text{panic}} = \text{mean}(\frac{1}{e^{(\text{health}/\text{nervousness})}}, \frac{1}{e^{(\text{experience}/\text{nervousness})}}, \text{shock})$ , where the affect of nervousness on the outcome can be seen in the figures below.

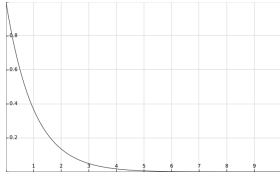


Figure 7: Panic component Function Curve: Nervousness = 1,  $x$ : Attribute Value,  $y$ : Component Score

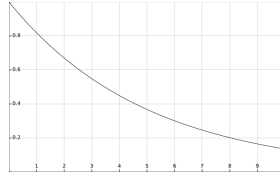


Figure 8: Panic component Function Curve: Nervousness = 5,  $x$ : Attribute Value,  $y$ : Component Score

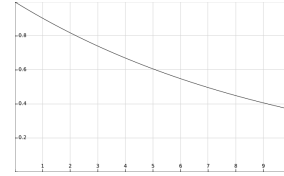


Figure 9: Panic component Function Curve: Nervousness = 10,  $x$ : Attribute Value,  $y$ : Component Score

- 3.3. If  $score_{\text{panic}} > 0.8$ , set mobility to 2 (panic movement).
4. Mark the current tiles in vision which are not obstructed by smoke or fire tiles, as known.
5. If there is a fire escape within the agent's knowledge grid, set the exit's coordinates as the target destination. If more than one exit is known, choose the exit with the shortest path.

## 6. Check collaboration

- 6.1. Calculate  $cost_c = mean(\frac{1}{e^{count_c+1}}, score_{panic})$ , where  $count_c$  is the collaboration count and higher values decrease the chance of collaboration. The function of the component can be seen below.

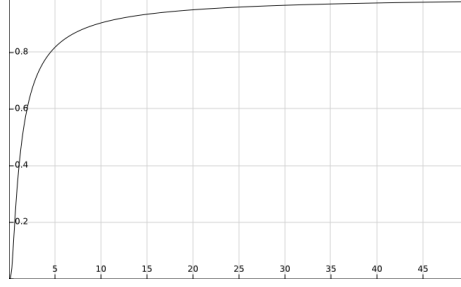


Figure 10: Component Value,  
 $x$ : Collaboration Count,  
 $y$ : Probability of not collaborating.

- 6.2. If a fire exit is in view, test  $cost_c$  and if it succeeds initiate verbal collaboration at the current location.
- 6.3. If another agent is in view and their mobility is 2 (panic movement), test  $cost_c$  and if it succeeds, set the agent as target for morale collaboration.
- 6.4. If another agent is in view and they are incapacitated, test  $cost_c$  and if it succeeds, set the agent as target for physical collaboration.

## 7. Movement

- 7.1. If the agent is panicking, test their panic score and if it succeeds, set the target location to a random location (panic movement). Or if their panic score was above 0.9 (90%) make the agent incapacitated (fainted).
- 7.2. If the target location is in sight, find the shortest unblocked path towards it.
- 7.3. If the target location is not in sight, perform a depth-first search towards it.
- 7.4. If there is smoke or fire in the agent's visible path and they don't have an action planned, change the path to retreat away from the danger.
- 7.5. Move along the planned path to the target destination according to the agent's speed value.
- 7.6. If we reached our destination and had a target action (such as collaborating) perform the action on arrival.

## 4.3 Experimental Setup

For our model tests, we attempt to replicate the setup parameters used in the Netlogo tests, so that we can achieve the most homogeneous comparison possible.

### 4.3.1 Fixed Parameters

#### 4.3.1.1 Fixed Model Parameters

- Floor-Plan: We use the same floor-plan as shown in figure 6 for all of our test runs.
- Number of humans: 200
- Probability of fire: 0.8
- Random human locations: True

#### 4.3.1.2 Fixed Human Parameters

- Health: Random value between 0.75 and 1.0
- Speed: Random value between 1 and 2
- Nervousness: Random value between 1 and 10, according to a distribution slightly favoring higher values.
- Experience: Random value between 1 and 10.
- Believes Alarm: Random according to a distribution of [True: 0.9, False: 0.1].
- Vision: Random value between 1 and 50, according to a distribution of vision impairments from the Worldwide Health Organization [3].

### 4.3.2 Variable Model Parameters

- Percentage of humans collaborating: Varied between 0% and 100% in steps of 10%.

## 4.4 Results

Due to the computational complexity of this simulation, we chose to process results from 100 iterations, which is substantially lower than the iterations made in Netlogo. This had to be done due to the time complexity of each agent, with each simulation easily taking 15 minutes. Running tens of thousands of simulations is therefore not currently feasible.

### Evacuation Success: 200 Human Agents, 100 Iterations

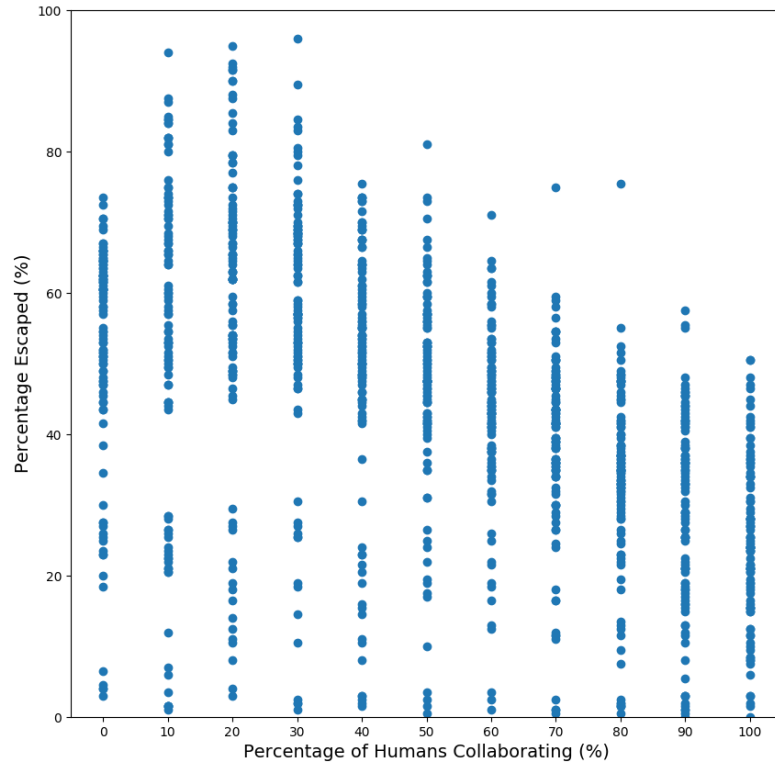


Figure 11: Scatter graph showing the percentage escaped, across varying intervals of collaboration percentage.

By calculating the means of each interval, we observe that the 20% interval yields the highest average success rate.

To attempt to understand why 20% collaborating yields the highest mean value, we take statistics from an example run which is close to the mean of that interval.



Percentage Collaborating: 0%, Number of Human Agents: 200

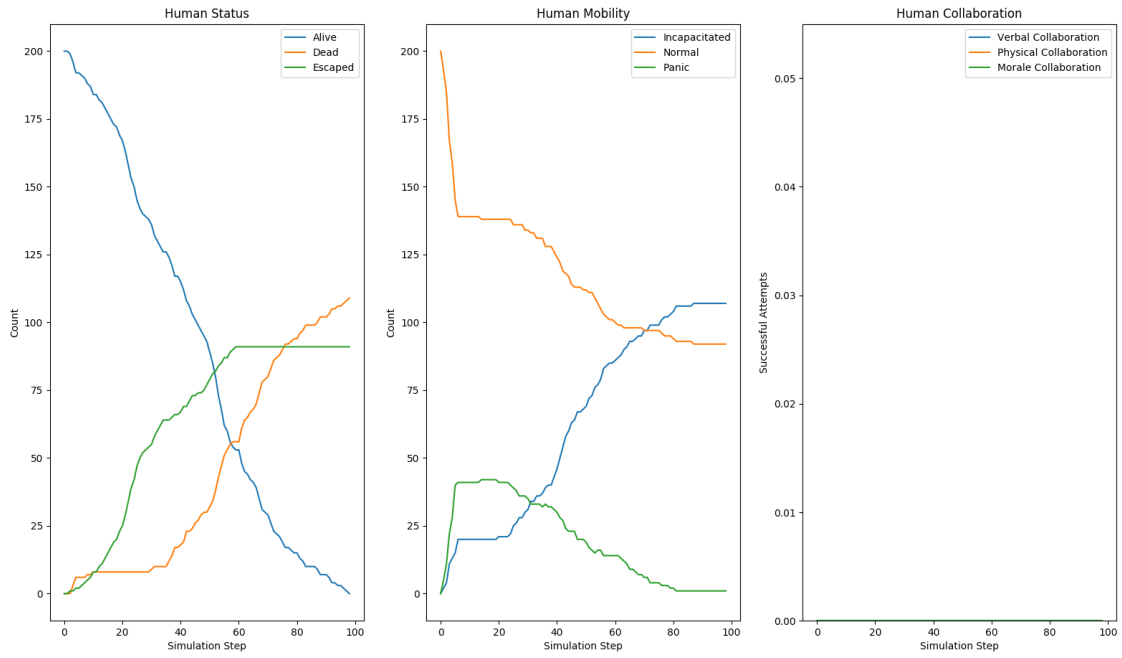


Figure 12: A simulation with 0% collaboration, matching the mean percentage escaped for this interval.

Percentage Collaborating: 20%, Number of Human Agents: 200

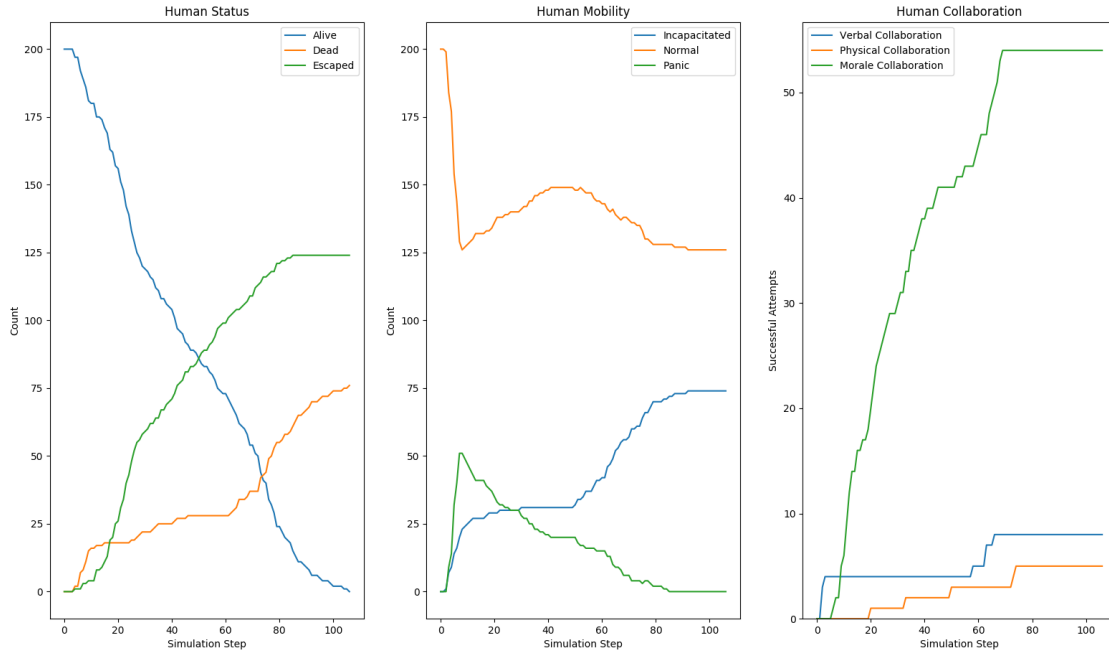


Figure 13: A simulation with 20% collaboration, matching the mean percentage escaped for this interval.

Percentage Collaborating: 100%, Number of Human Agents: 200

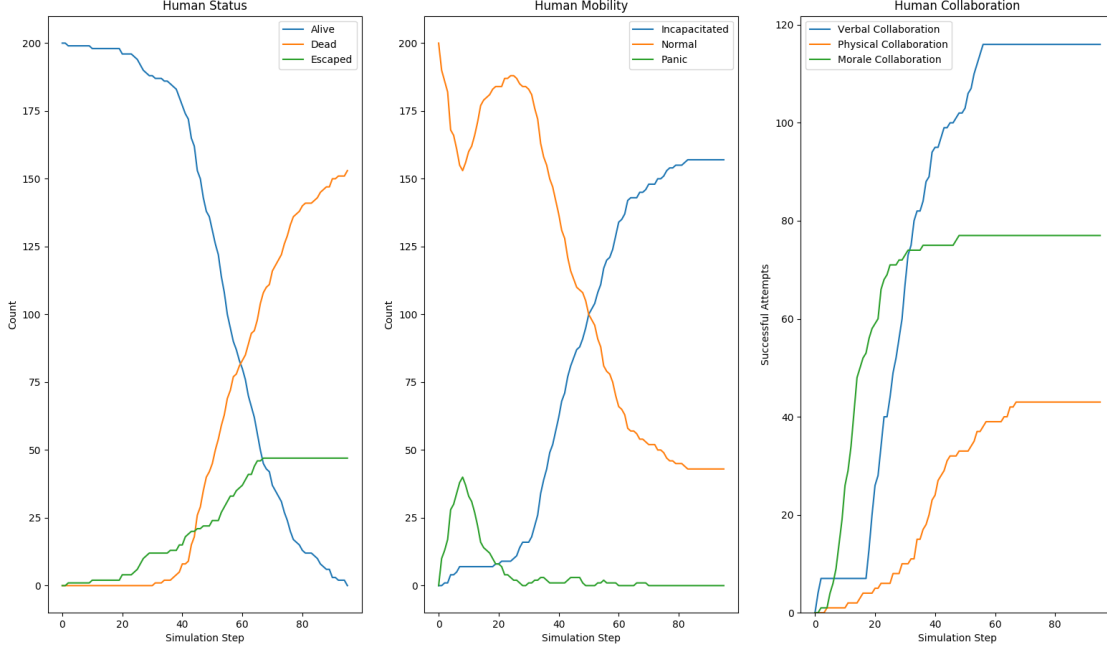


Figure 14: A simulation with 100% collaboration, matching the mean percentage escaped for this interval.

From figure 13 we observe a greatly higher ratio of morale collaboration than any other type, when compared to figure 14 which has verbal collaboration as the most occurring type. Surprisingly, all three figures show approximately the same number of panicking agents. What does differ however, is how quickly the panicked agents are calmed down. One other notable difference is during the 20% simulation, many more agents died early on than in the other simulations.

## 5 Conclusion

Studying the results of the NetLogo model on figure 15, it is evident that the mean escape success percentage rises with the increased amount of helper agents. After a sum of helpers amounting to 50% of the total amount of people, there is an approximate stabilization on high escape percentage. However, a higher amount of outliers representing lower success rates is present, suggesting that a higher amount of helpers is not totally reliable in regards to survival. Overall, the results of the NetLogo model are in accordance with our hypothesis.

The results of the Mesa model (see figure 16) demonstrate some interesting notions. There is no linear correlation between the percentage escaped and the percentage collaborating, as we were expecting. Intervals up to 30% collaboration, have a positive impact on the mean evacuation success. From then on-wards, we observe a linear decrease of mean values.

In terms of common sense, it would be expected that the amount of helpers positively affects the success rate, as per our hypothesis. Interestingly, the Mesa model which simulates an evacuation based on more realistic environmental and behavioural variables, yields almost the opposite result. An explanation for this could have its roots in the experience of the people that initiate collaboration, as in this model it has been realized only in reference to the state of panic. This leaves out a lot of aspects of experience observed in real life situations, where emergency training is involved. It would be interesting for this model to be enhanced with experience related heuristics in the future, to test whether the decrease in escape success still holds.

Evacuation Success: 200 Human Agents, 2000 Iterations

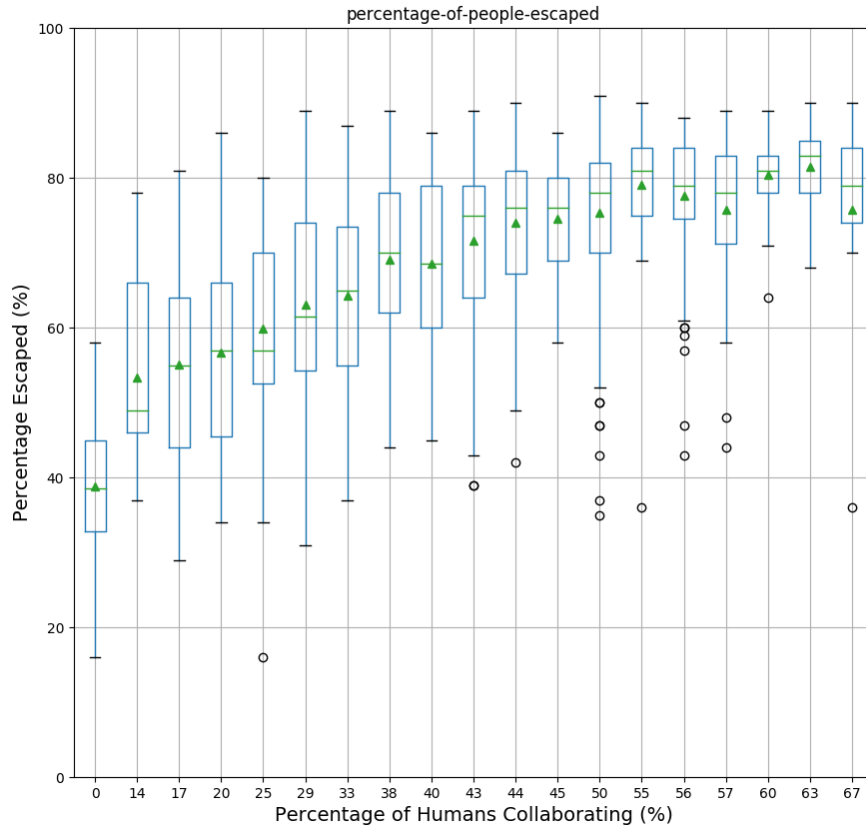


Figure 15: Overall results of the NetLogo iterations

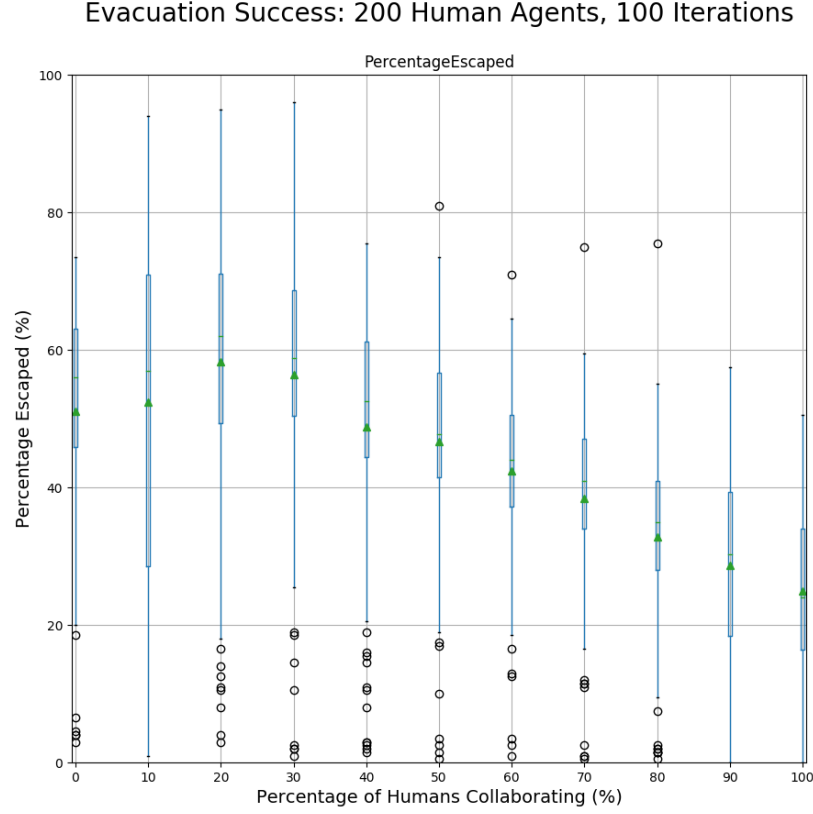


Figure 16: Overall results of the Mesa iterations

## References

- [1] João Emílio Almeida, Rosaldo J. F. Rossetti, and António Leça Coelho. “Crowd Simulation Modeling Applied to Emergency and Evacuation Simulations using Multi-Agent Systems”. In: *CoRR* abs/1303.4692 (2011). URL: <https://arxiv.org/pdf/1303.4692.pdf>.
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