Modeling human factors influencing herding during evacuation

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Modeling human factors influencing herding during evacuation

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Abstract

Purpose – It has been witnessed that many incidents of crowd evacuation have resulted in catastrophic results, claiming lives of hundreds of people. Most of these incidents were a result of localized herding that eventually turned into global panic. Many crowd evacuation models have been proposed with different aspects of interests. The purpose of this paper is to attempt to bring together many of these aspects to study evacuation dynamics.

Design/methodology/approach – The proposed agent-based model, in a hypothetical physical environment, uses perception maps for routing decisions which are constructed from agents' personal observations of the surroundings as well as information gathered through distant communication. Communication is governed by a trust model which measures the authenticity of the information being shared. Agents are of two types; emotional and rational. The trust model is combined with a game-theoretic model to resolve conflict of agents' own type with that of types of agents in the neighborhood.

Findings – Evacuation dynamics in different environmental and exit strategies are evaluated on the basis of reduced herding and evacuation time. Using this integrated information sharing model, agents gain an overall view of the environment, sufficient to select the optimal path towards exits with respect to reduced herding and evacuation time.

Originality/value – The proposed model has been formulated and established using an agent-based simulation integrating important modeling aspects. The paper helps in understanding the interplay between technological and humanistic aspects in smart and pervasive environments.

Keywords Simulation, Modeling, Crowd, Herding, Ambient intelligence

Paper type Research paper

1. Introduction

In the past few decades, natural calamities such as floods/tsunamis and earthquakes have increased in number. Along with these, humanity is also facing regular instances of human-generated disasters, such as collapsed buildings and terrorists attacks. Mostly, during these situations, the behavior of humans facing the situation becomes more problematic than the destruction induced by the event itself. For example, it has been observed that *herding* is the main reason of deaths in crowd disasters Wang *et al.* (2015). Recently, such unfortunate situations have also been observed in mass gatherings for festivals[1] and religious gatherings[2].

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The purpose of studying crowd evacuation dynamics is to be able to direct people in an efficient and calm manner towards an exit point during these disasters. The success of an evacuation process is dependent on multiple aspects of crowd dynamics as a whole and at an individual level. These aspects are based on internal and external factors. Internal factors are based on social attributes and the psychological nature of human beings, while external factors are based on the surrounding environmental attributes such as confinement area, obstacles and danger zones. These factors collectively help in the study of a realistic evacuation procedure aimed at mitigating the threat to human life and property. Crowd behavior in an evacuation scenario is implemented using simulation techniques.

While modeling a system for crowd evacuation, the question of entirety, i.e. encompassing both internal and external factors, becomes relevant. Another question is about the modeling resolution – macro level vs micro level (Nguyen *et al.*, 2012; Zheng *et al.*, 2009). Macroscopic models focus on crowd behavior as a whole rather than considering individual beings (Yanfei and Yonglin, 2011). Collective attributes are considered such as density of crowd and average speed of crowd in a specific area (Gerritsen, 2011). Previous works are based on models concentrated on overall behavioral characteristics of a crowd such as in Sharpanskykh and Zia (2012) and Zheng and Cheng (2011). Simulating macro level models have the advantage of minimal amount of computing as it considers the crowd as a single entity (Nguyen *et al.*, 2012). In contrast, micro level models focus on the internal characteristics of each human as well as their local interaction with the surrounding people (Zia *et al.*, 2011). These characteristics include emotional and psychological factors that influence individuals' decision-making (Gerritsen, 2011; Haciomeroglu, 2016). These decisions are not only based on their own perceptions but also influenced by the neighbors. With advancements in computing capabilities and development of agent-based modeling (Nguyen *et al.*, 2012) into a mature knowledge domain, it is now possible to efficiently model a microscopic simulation. This enables analysis of human behavior at the individual level which helps in an insightful study of a localized behavior potentially emerging into a global disaster.

Agent-based modeling has been established as a suitable modeling technique. This paper focuses now on the crowd evacuation models that are categorized as follows:

- *Structural models*: These models focus on the relationship of geometry of the environment with crowd density. The main focus of these models is to divert crowd from a structurally less to a more feasible situation. This can easily be achieved using a macroscopic modeling technique.
- *Individual models*: These are the models in which individuals have local knowledge of their surroundings only and they take decisions solely based on it. Typically, these are simplistic agent-based models.
- *Hybrid models*: These are the models in which agents augment their information with external information they may get from other peers at a distance or from a centrally connected server. These models typically discuss the role of ICT in an emergent society.
- *Social models*: These models focus on the social aspect of human behavior and cognition. The effect of the type of population on decision-making along with evolution of personal traits such as trust and belief while an agent is socially interacting with others are the issues addressed by these models.
- *Game-theoretic models*: The role of rationality in decision-making is relevant and critical to evacuation situations and addressed by these models.

All the above models address different aspects relevant to crowd evacuation dynamics. Integrating these aspects into a combined model is still a challenge. In this paper, challenges regarding the disastrous effects of herding are addressed by developing an agent-based model that simulate evacuating a crowd. The herding effect is a type of behavior of a crowd in a state of panic under the influence of pure emotions, which often results due to blindly mimicking others (Zia *et al.*, 2016).

In contrast to the above-mentioned isolated models, the model proposed in this paper integrates multiple aspects into one combined model. Starting with ICT as the base capability available, the agents in the proposed model not only have local information but also have a partial view of information about distant regions. With this they build a mental map about different regions in the environment. However, the information attained from peers cannot be fully trusted, particularly when evidencing a contradiction in the locality. Hence, it is necessary to evaluate the information received by a trust model before making a decision. Agents' individualistic traits are further incorporated in the model by introducing a game-theoretic model of rational choice.

The rest of the paper is organized as follows. The paper starts with related work in Section 2. A model of routing decisions based on regional densities perception is presented Section 3, followed by the Trust model. Section 3 also describes the Locomotion model. Section 3 ends with a game theoretic model which affects the routing choice based on conditions in the proximity of an agent. Section 4 deals with simulation settings and exit strategies, ending with an analysis of the simulation results. Section 5 concludes the paper.

2. Related work

Agent-based models for improvement of evacuation efficiency, focusing on different aspects of interest, have been proposed by Ferscha and Zia (2009), Popescu *et al.* (2013) and Wang *et al.* (2016). In Nguyen *et al.* (2012) and Lin *et al.* (2012), path planning is based on road network, Qin and Wei (2010) is simulated on a train station, Zhang *et al.* (2015) is a model for evacuation of office building, while others simulated for public places are Solmaz and Turgut (2015) and Wang *et al.* (2014). To model microscopic behavior, laws based on Physics (Ferscha and Zia, 2010; Gerritsen 2011; Zheng and Cheng, 2011) or Cellular Automaton (CA) (Wang *et al.*, 2014; Ferscha and Zia, 2009; Fu *et al.*, 2014; Zia *et al.*, 2016; Zhang *et al.*, 2015; Tang *et al.*, 2015) have been used.

However, using physical models may not be enough. More often, the emotional characteristics of a person influence their decision-making. Studying crowd behavior is deeply concerned with the humanistic expressions and responses based on feelings and emotions. In Liu *et al.* (2009), the influence due to the sentiments of each agent in a crowd has been mapped. Making use of Helbing's model for crowd movement (Helbing and Molnar, 1995), the authors' simulation results show that people with negative emotions tend to explore more virtual space but reach their destination in more time as compared to those with positive emotions.

Emotions often lead people to bad decisions due to panic and irrational thinking. One of the effects observed due to such panic induced decisions is the emergence of herding (Raafat *et al.*, 2009). Herding causes a major impact on evacuation dynamics. This effect does not only results in slower evacuation but in severe cases also causes deaths (Zia *et al.*, 2016). To study the cognitive science behind herd behavior, many approaches have been proposed to elucidate and minimize its effects. Ramsay *et al.* (Raafat *et al.*, 2009) define herding as a result of lack of central coordination. Two models based on transmission of thoughts and pattern of interconnection between individuals, to understand how cognition plays a role in herd behavior, are studied in detail.

Trust is an attribute that caters to one's choice of route on reliability of source information (Farrahi *et al.*, 2013). Evacuation guidance can be optimized by considering the human psychological characteristics. In Lu *et al.* (2014), the authors suggested that path familiarity, guidance information, herd behavior, nervousness and other factors such as investigative and cooperative behaviors, impact the selection of the path to exit.

It is evident from the literature that not many studies cover the effects of information spread through mobile communication or sensory technology. The few papers that are based on such ambient intelligence (AmI) systems do not involve humanistic nature, such as psychological aspects, that could lead to different results. These studies assume a steady movement of users according to some set of rules, whereas in real scenarios, people often deviate from their path due to their emotional mental state. One such effort has been made in our previous work, Farrahi *et al.* (2013).

Game-theory can naturally model the conflicting versus cooperating behaviors between individuals in decision-making. One such research has been performed in Crociani *et al.* (2015). In this paper, the authors build up a game on the basis of two behaviors exhibited by a rational agent: vying and polite behavior. In evacuation emergencies, people often exhibit the tendency to cooperate or compete. Such behavior effects the evacuation time tremendously. Similar to their previous work (Zheng and Cheng, 2011), Zheng and Cheng have modeled the cooperative versus competitive behavior of rational agents, using game-theory. Motivated from their work, a model to analyze interplay between emotions and rationality is proposed to reduce the effect of herding (Zia *et al.*, 2016) during evacuation.

In this work, a combined model of crowd evacuation is proposed, with the goal of symmetric utilization of resources in terms of exit usage and evacuation time. The model will provide game-theoretic decision support to the agents, along with a model relating the crowd behavior in AmI environments with the model of information sharing. The information sharing is directed by trust in the information model.

3. Models

Multiple aspects are integrated into one combined model (Section 3.5). The route selection model (Section 3.1) is an information-directed model (more the information an agent has, more are its chances of avoiding congestion). The environment is an AmI environment, possibly having various interaction and information exchange modalities. The trust model (Section 3.2) operates with the above model of information sharing and perception building, consequently affecting the model of physical mobility/locomotion (Section 3.3). Finally, agents' individualistic traits are incorporated in the model by introducing a game-theoretic model of rational choice in which payoff of rational agents is higher when they act to avoid local congestion (Section 3.4).

3.1 Route selection model

An agent-based model based on physical attributes of the environment, such as direction, distance and region-based routing, is used to build a perception map of agents (Farrahi *et al.*, 2013). Equal size regions constituted by equal sized cells are used. For each exit, densities are calculated along the route consisting of average densities of all regions along a particular route:

$$\rho(exit_i) = \sum_{e=1}^{N} \rho(region_e)/N \tag{1}$$

The average density for a particular exit is weighed in conjunction with the distance parameter, d, as:

$$\omega(exit_i) = \rho(exit_i) \times d(exit_i) \tag{2}$$

The exit selected is one with minimum weight over the route to exit:

$$exit^* = Min(\omega(exit_i)) \tag{3}$$

Each agent knows the density of the region it resides in and assumes the same for all other regions in the absence of information sharing. However, communication with other agents is possible. Proximity communication is physically interacting with agents within a range (its neighborhood). Distant communication is interaction at a distance through some medium, such as a cellular network. After interaction, the perception map of an agent may be updated based on the trust model described next.

3.2 Trust model

An agent would act upon the information received from a peer (in neighborhood or at a distance) on the basis of the trust on the source information. This trust is evaluated in relation to the agent's beliefs. Given this reasoning, a decision model is formulated. The decision towards a choice of exit depends on the time taken to reach a particular exit. This time is affected by the length of the path and the speed of the agent in relation to the densities along the regions. The density of regions is continually updated due to movement of agents. Hence, the level of trust about densities of the region shared by peers is given by:

$$B^*_{\rho_r,j} = \frac{C_{\rho_r,i} T_{j,i} B_{\rho_r,i} + C_{\rho_r,j} B_{\rho_r,j}}{C_{\rho_r,i} T_{j,i} + C_{\rho_r,j}} \tag{4}$$

where * denotes value at next iteration and $T_{j,i}$ represents agent j's trust towards agent i. Moreover, $T_{j,i}$ is updated as:

$$T_{j,i^*} = T_{j,i} + \alpha\left(C_{\rho_r,j} \frac{1}{1 + e^{-\gamma|B_{\rho_r,j} - B_{\rho_r,i}| + \beta}} - T_{j,i}\right) \tag{5}$$

where T is trust, C is for confidence and B is belief.α, β and γ are constants. $C_{\rho_r,i}$ reflects the confidence of agent i on density information of region ρ_r.When this information is shared by agent i with j, then confidence of agent j is updated as follows:

$$C^*_{\rho_r,j} = \frac{C_{\rho_r,i} T^*_{j,i} + C_{\rho_r,j} T^*_{j,j}}{T^*_{j,j} + T^*_{j,i}} \tag{6}$$

Assuming every agent completely trusts itself, $T^*_{j,j} = 1$.

3.3 Locomotion model

The movement of agents is modeled based on Moore's neighborhood in which agents can move to one of the eight neighboring cells. If a cell is occupied then the agents can choose to move to the next cell in the direction of motion and so on, as shown in Figure 1. The locomotive behavior of agents is described using three variables which are as follows:

(1) *Mobility index (MI)*: Records the incremental value of an agent's mobility. Whenever an agents moves to another cell according to Figure 1, the value of the MI will be incremented. For instance, when an agents moves from one cell as in Figure 1(b) to another as in Figure 1(c), the value of MI will be one more than in the previous iteration. If an agent is mobile, then the below two variables will be set to 0.

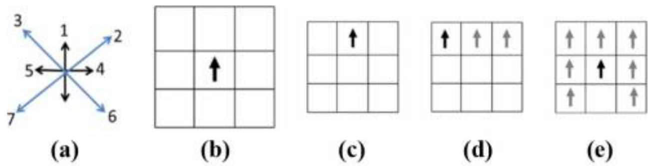
(2) *Waiting index (WI)*: Records the incremental value of an agent unable to move to another cell. For example, in Figure 1(e) all the neighboring cells are occupied, hence the WI will be incremented by 1 whereas MI will be reset to 0.

(3) *Panic index (PI)*: Records a value showing that an agent is in a state of panic. This is in accordance with the WI such that if an agent is unable to move for a certain iteration, then its PI will be incremented.

3.4 Rational decision-making model

A rational agent is an agent who has the capacity to make a rational choice based on current information that it possesses. An emotional agent is entirely opposite of it, driven and herded by the crowd in the surrounding. A rational agent can also be interactive, able to communicate with peers at a distance and share information.

This model is based on the game-theoretic approach. Player 1 acting as an agent is the one taking the decision towards an exit, whereas Player 2 is a random agent acting as the influencer with whom distant connection is formed through communication as described in the perception model. If Player 1 is emotional and its behavior is similar to that of Player 2, then maximum pay-off is achieved and Player 1 tends to retain its behavior. In case the behavior of Player 1 is contradictory to Player 2, then the pay-off remains maximum but with a slight probability of 10 per cent that Player 1 might change its decision depending on the value of PI ($PI > 0$).



Notes: (a) Directional preferences of an agent with intended direction labeled 1; (b to c) move of agent at the center to the unoccupied cell in intended direction; (b to d) move of agent at the center to the unoccupied cell NOT in intended direction and in accordance with the directional preferences; (e) inability of agent at the center to move due to occupancy of all the cells in accordance with the directional preferences

Figure 1.
Next cell selection criteria strategy explained

In case Player 1 is a rational agent, the outcome depends on its state of being in panic or not. If a rational agent is not in panic then observing similar behavior in a random agent will result in strengthening of its own belief, thereby getting maximum pay-off, but there exists a 10 per cent chance of the rational agent being deviated from its path. Contrary to this, if the rational agent's behavior is opposite to that of the random agent then it will weaken the belief on its current behavior, resulting in minimum pay-off, hence there is a 90 per cent probability that Player 1 will change its choice of exit.

In the last scenario, where Player 1, being rational, is in a state of panic and observes similar behavior of Player 2, it will result in minimum pay-off. This will lead to the agent strictly changing its exit. Similarly, if the behavior of Player 1 is inconsistent with that of Player 2, then maximum pay-off is gained, allowing the agent to retain its current behavior. This game has been elaborated in Figure 2.

3.5 Combined model

A generic representation of the combined model has been illustrated in Figure 3.

If an agent is rational and interactive, the Route selection model would be changed as described below.

The agent would communicate with a random interactive agent. The communication would be governed by the trust dynamics between the agents (Trust model). Based on the confidence value of the interacting peers, a weight to each of the possible exits would be calculated based on:

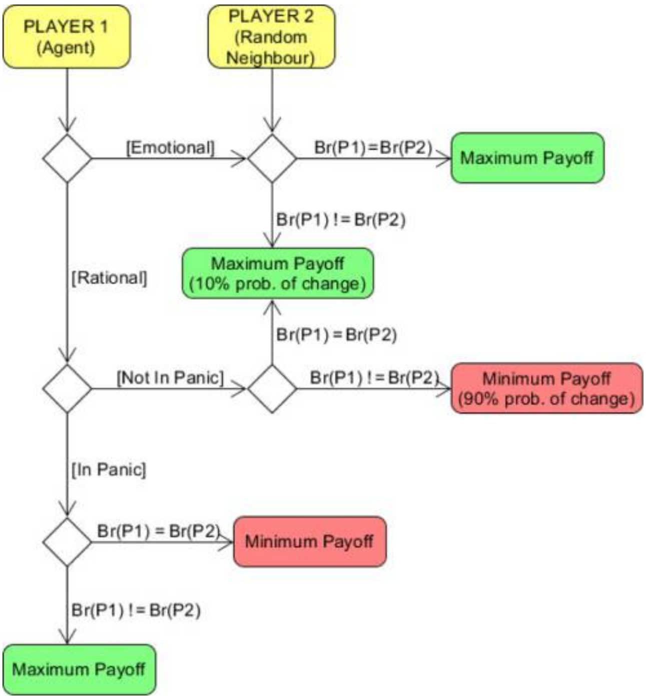


Figure 2.
Game-theoretic model of rational decision-making

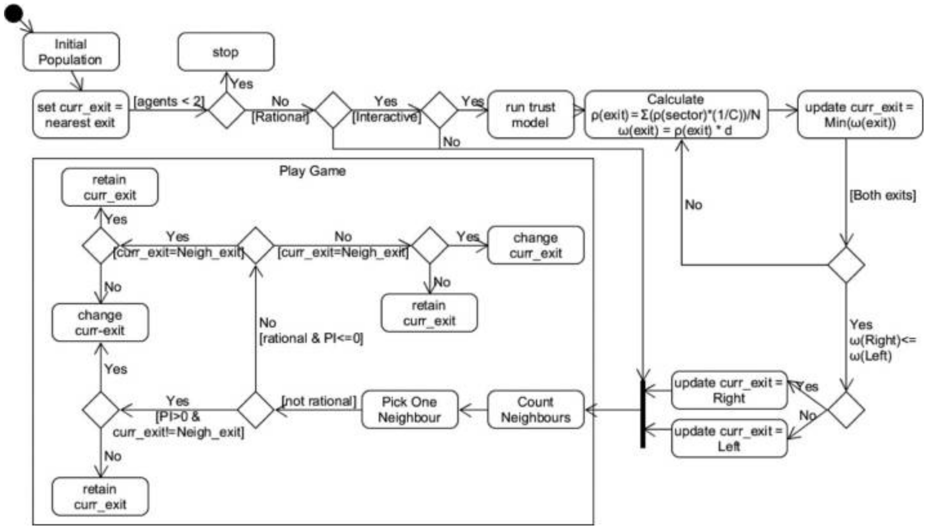


Figure 3.
Flow diagram of combined model

$$\rho(exit_i) = \sum_{e=1}^{N}(\rho(region_e) \times (1/C(region_e))/N \quad (7)$$

where ρ of the region is the perceived density of region r, which is weighted with inverse of confidence of agent on that region.

The densities of all the regions along the route (calculated based on nearest measure) from one to N are summed together and averaged to assign value to each exit. The inverse relation with confidence will ultimately lead to the route with high confidence and the agent selects the path with minimum value using equations (2) and (3). The Rational decision-making model would then be executed.

If the agent is rational and not interactive or the agent is not rational, it would just execute the Rational decision-making model after application of the Route selection model.

All agents would be under the influence of Locomotion model for each next step decision.

4. Simulation settings

Agent-based simulation is used to inquire about several "what-if" questions. The questions asked focus on the type of simulation environment (Section 4.1), density and distribution of agent population (Section 4.2) and strategies/mechanisms that agents may use to exit the environment (Section 4.3).

4.1 Simulation environment

NetLogo is used as a simulation tool (Wilensky, 1999). The simulation setup is based on a grid of cells of dimension 51 × 51. The space is divided into 25 evenly distributed regions. The agents occupy the cells and their movement is dependent on information of neighboring cells. For this purpose, floor field has been used to identify the nearest exit using distance and direction measures. Initially, all the agents acquire nearest exit as chosen exit (*current exit*). The *current exit* may change after application of the model presented in the previous section.

The spatial environment consists of two exits. Three cases of exit distribution have been defined in Figure 4:

(1) *Symmetric (E1)*: Symmetric distribution indicates that the number of cells closer to the left exit are equal to those on the right exit.

(2) *Asymmetric (E2)*: Asymmetric means that the number of cells closer to the left exit are not equal to those on the right exit.

(3) *Hidden (E3)*: Hidden means that the exit is not visible due to some obstacle or wall, shown in grey.

4.2 Agent population

Different distributions of agents have been simulated to test the model. The three cases are:

(1) *Sparse*: 500 agents.

(2) *Medium*: 1,000 agents.

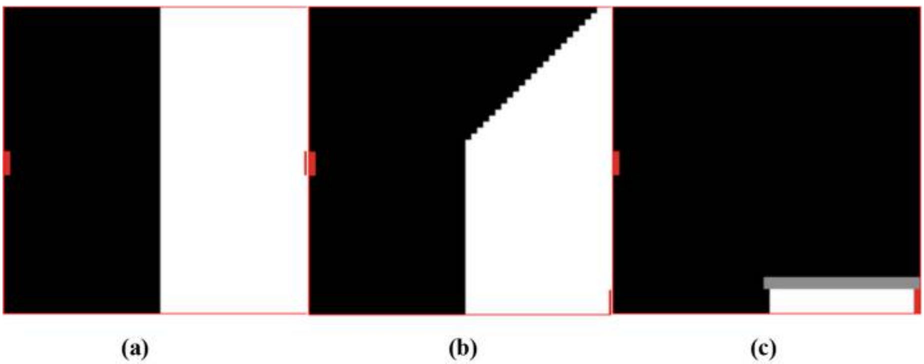
(3) *Dense*: 1,500 agents.

In each simulation case (environment type and agent population), rational agents are 10 and 25 per cent of the total population, while the remaining are emotional agents. The interactive agents' population has been considered to be 25, 50 and 100 per cent of the total population of rational agents. A view of agent types and population is depicted in Figure 5.

4.3 Exit strategies

The following exit strategies are used:

- *Strategy 1 (S1): Nearest exit*: The agents initially select their exit based on this strategy. Selecting the nearest exit is based on the distance to each of the two exits, and quantified as:



Notes: (a) Symmetric: the number of cells closer to the left exit (shown in black) is equal to the number of cells closer to the right exit (shown in white); (b) asymmetric: the number of cells closer to the left exit (shown in black) is not equal to the number of cells closer to the right exit (shown in white); (c) hidden: a limited number of cells are closer to the right exit (shown in white) due to its invisibility because of an obstacle, for example a wall (shown in gray)

Figure 4. Geometrical variation of two exit shown in red

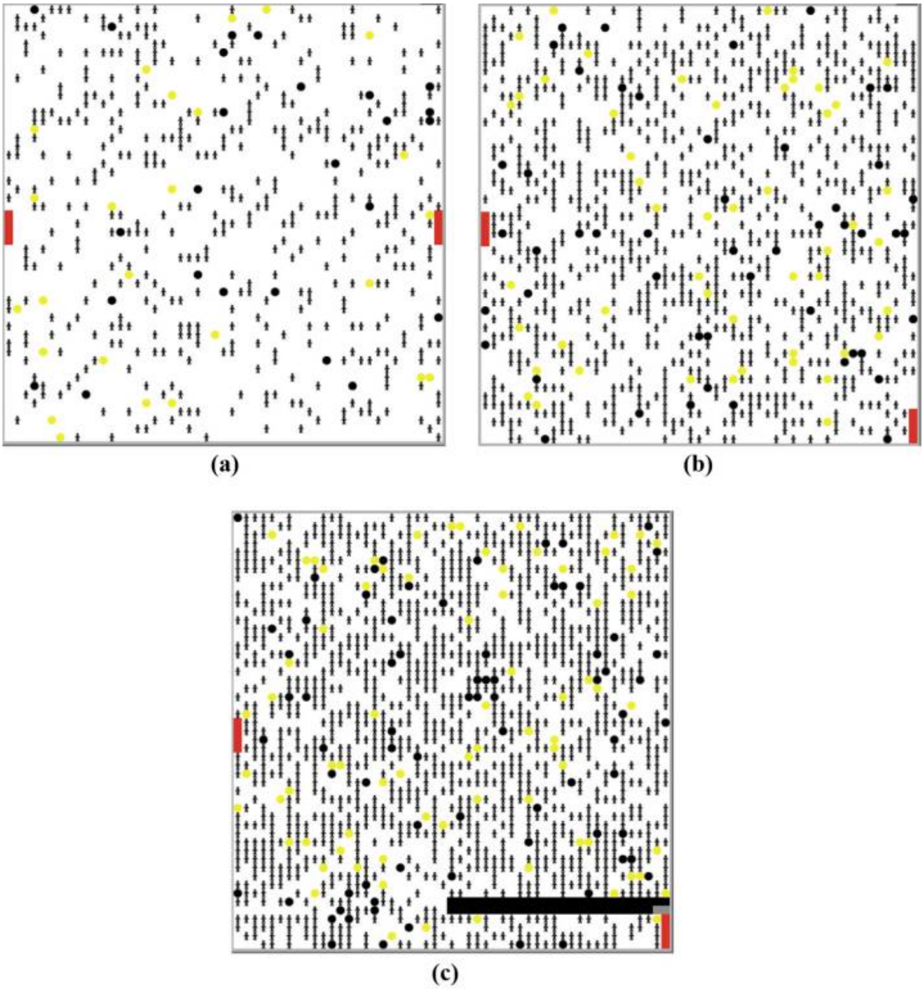


Figure 5.
The space with variable agents' population and varied environment types

Notes: Ten per cent agents are rational represented by circles, whereas 50 per cent are interactive represented in yellow color; rest of them are emotional agents; (a) 500 agents in symmetric environment; (b) 1,000 agents in asymmetric environment; (c) 1,500 agents in hidden environment

$$exit^* = Min(d(exit_i)) \tag{8}$$

where d is the distance towards the exit.

- *Strategy 2 (S2): Least congested route*: In this strategy, agents will perceive their surroundings using personal observation about the density of agents in the different regions along the route to exit. This will allow the agents to change their choice of exit when they find their existing route to be more crowded than the other. To calculate the least congested route, equations (1)-(3) are used.

- *Strategy 3 (S3): Least congested route through interaction*: Communication with distant peers to get updated information about the evacuation space is a vital part of this study. This strategy allows agents to switch exits based on information sharing about regions with each other. This interaction will only be among the interactive agents of the population. The information shared gives a distant and possibly updated perspective to agents' perceptions about the environment while calculating the least congested route using equations (1)-(3).
- *Strategy 4 (S4): Route based on peer pressure*: Using strategy 3 as the underlying structure, an agent's decision will be re-evaluated according to the game elaborated in Section 3. This strategy facilitates the rational agents in selecting the exit based on maximum pay-off.
- *Strategy 4 Plus (S4+): Route based on peer pressure*: This strategy is another version of strategy 4 which allows agents to change their choice of exit more than once while moving towards an exit.
- *Strategy 5 (S5): Route based on interaction and trust*: This strategy incorporates the role of trust, belief and confidence on an agent's decision of selecting an exit. These attributes associated with agents are updated using the equation of trust model described in Section 3 [equations (4)-(6)]. The agents select the route with low density and high confidence value [equation (7)].
- *Strategy 6 (S6): Route based on combined model*: This strategy incorporates all the factors relating to interaction, peer pressure and cognitive abilities in selecting a path towards the exit. The strategy, diagrammatically shown in Figure 3, is similar to strategy 4 except that it considers strategy 5 as the baseline structure and then executes the game-theoretic model.
- *Strategy 6 Plus (S6+): Route based on combined model*: In this scenario, agents will be allowed to change their exit selection more than once while following strategy 6.

5. Analysis of simulation results

5.1 Analysis parameters

The following parameters are used for analysis of the simulation results:

- *Ticks*: Specifies the discrete time denoted to each iteration of the simulation.
- *Using-left*: Percentage of agents using the left exit to evacuate.
- *Using-right*: Percentage of agents using the right exit to evacuate.
- *Max Ag. in panic*: The maximum number of agents that went into state of panic during the simulation.
- *Max PI value*: The maximum PI value of an agent at any time during the simulation.
- *Last-left*: The iteration at which the last agent escapes from the left exit.
- *Last-right*: The iteration at which the last agent escapes from the right exit.

5.2 Analyzing the exit strategies

To perform a comparative analysis of exit strategies, a population of 1,500 agents is chosen, with 10 per cent of rational and 25 per cent of interactive agents, in environment E3. Figure 6 shows the initial population considered for this section. From Figure 7, it is generally evident that evacuation time decreases as agents interact and update their perception map.

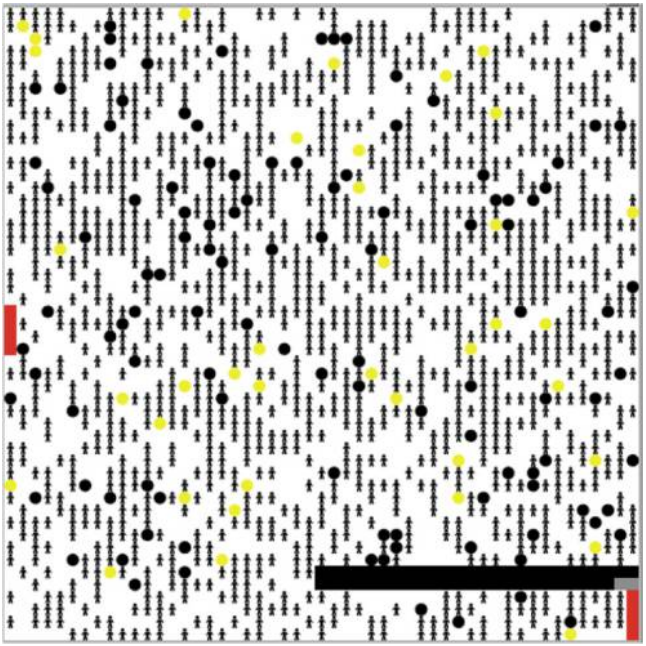


Figure 6.
Initial setting with 1,500 agents, 10 per cent rational and 25 per cent interactive agents

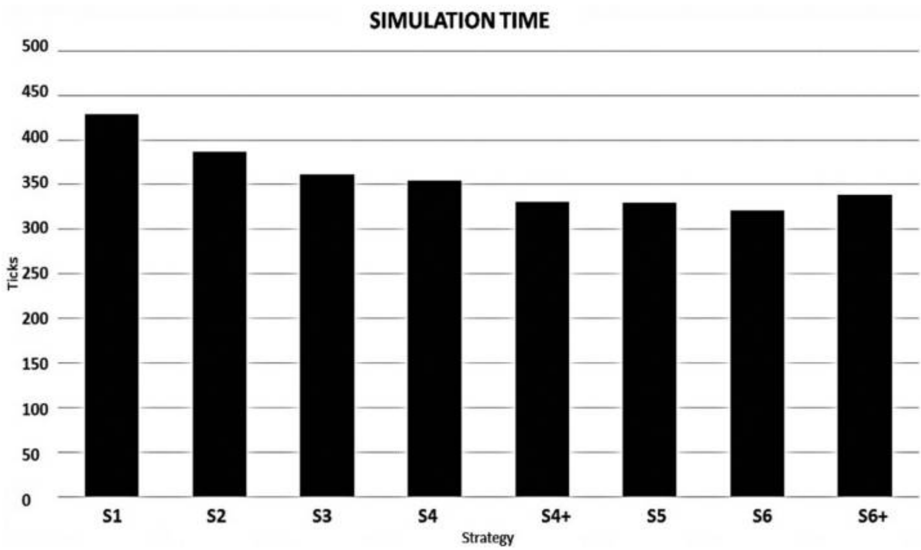


Figure 7.
Exit time for each exit strategy population of 1,500 agents with 10 per cent of rational and 25 per cent of interactive agents in E3

The difference in evacuation time (in terms of ticks) is seen from S1 to S3. However, S4 displays only a slight difference due to the reason that it considers the emotional and rational behavior of agents, which sometimes prohibits them from taking the optimal decision. S4+ significantly reduces time as it allows agents to change their exit more than once. Incorporating the trust model, S5 also displays a significant decrease in time when compared to S4 - this decrease is due to the involvement of choosing a route with high level of confidence in combination with low density. Although, strategies S6 and S6+ show marginal increase in exit time, they affect the other factors in a positive way.

In Figure 8(a), exit utilization results of the same scenario are shown. As one of the exits is hidden, an equal distribution of agents along the two exits is not possible. Looking at the strategies in comparison to S1, there is a significant increase in agent population exiting from the right exit. The reason for this is that agents try to move towards an exit with the least congested route rather than adopting the nearest exit.

In Figure 8(b), agents' distribution over the two exits has been analyzed for different strategies. In the graph, S1 display the worst distribution over the left and right exits as very few agents choose to exit from the hidden exit on the right. Incorporating accurate information over the different strategies, it can be viewed that agent distribution becomes significantly even. Strategy 5 displays the same iteration at which the two exits were last utilized by agents. In strategy 6, this difference is minutely increased mainly because it considers the behavioral model as well. S6+ does not show desirable results. The large difference is due to allowing agents to switch exits. Playing the game, agents choose to change their exit at the last moment on the basis of neighboring agents. As the majority of the population tends to exit from the visible exit of left, the emotional agents act in accordance with the majority and hence, the unbalanced distribution becomes inevitable.

Figure 9(a) displays the maximum number of agents in panic for each strategy. It is conspicuous that with increase in accuracy of information, the number of agents in panic decreases. The graph indicates strategy S6 as the best case for achieving low number of agents in panic. However, there is a phenomenal increase in panic-stricken agents in strategy S4+, this is due to the multiple exit change which can lead to global panic. There is also an increase in panicked agents in Strategy S5, this could be due to trusting an information source that turned out to be inaccurate.

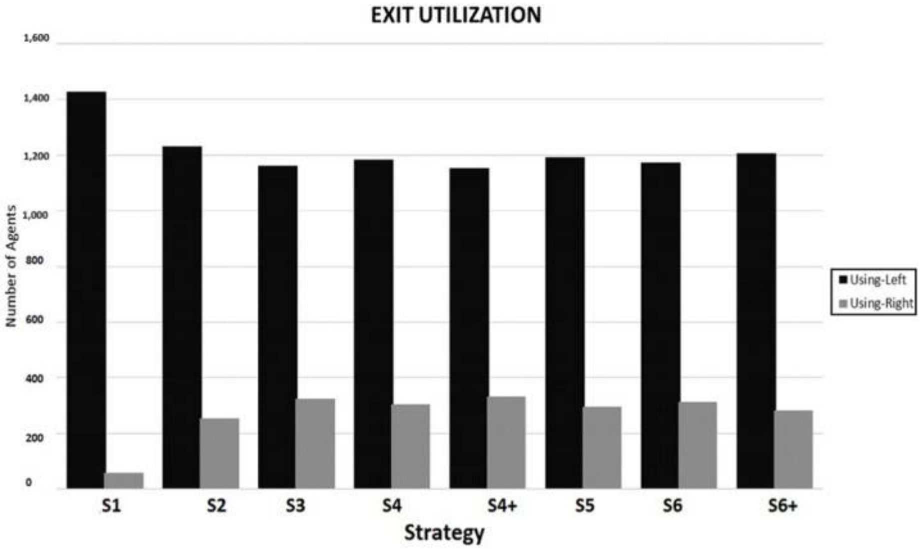
In Figure 9(b), the graph indicates the maximum iteration for which any agent in the population was in a state of panic. The reason to analyze this is crucial for old people or people with health issues. In a population of 1,500, if the acceptable scale for PI is assumed as 95, then using Strategy S1, S2 and S5 will be ineffective for such people and may cause their death. Overall, the combined model turns out to be the most effective strategy, which will allow people to escape with minimal time, minimal number of agents in panic as well as maintain the PI value below the threshold with an acceptable distribution of agents on both exits.

To observe the difference in panic among agents, a screen-shot for each strategy showing the number of agents at the same iteration has been taken (Figure 10). This will help to visualize the agents in waiting mode and how that wait state eventually leads agents into panic.

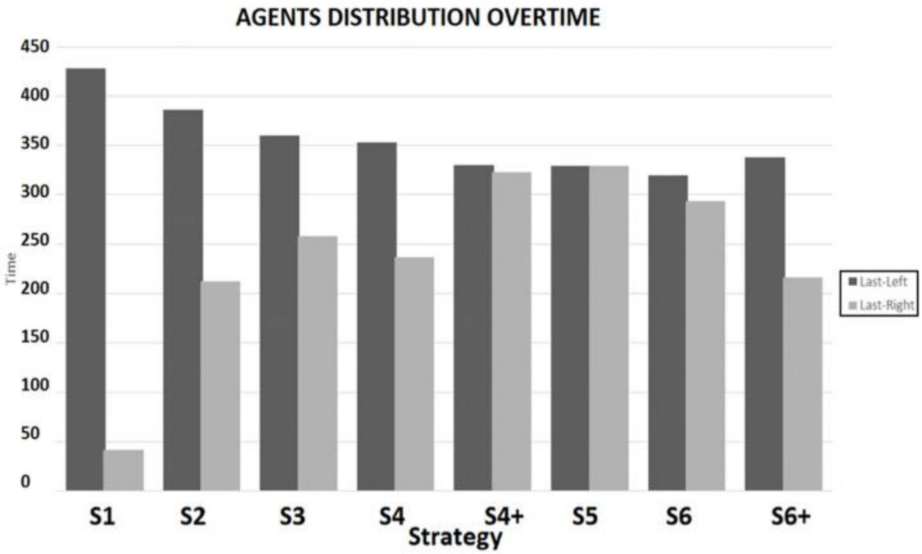
5.3 Analyzing the environment types

To analyze the difference in evacuation behaviors in three environment settings, the simulation was performed for 1,000 agents with 10 per cent rational and 50 per cent interactive agents. Here, E1 refers to symmetric, E2 refers to asymmetric and E3 is hidden as illustrated in Figure 4. In each environment, all strategies (i.e. S1-S6+) are observed.

In Figure 11, time taken for agents to evacuate using different strategies in different environments has been displayed. Comparing times across different environment, it can be observed that environment E1, with symmetrically aligned exits, has significantly low



(a)



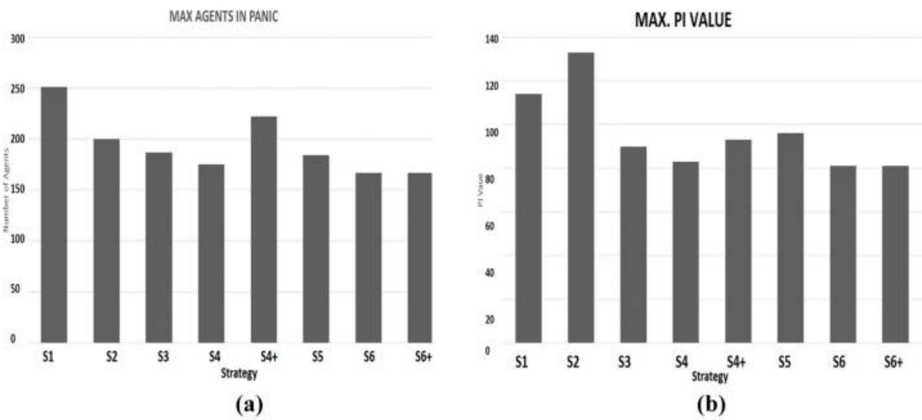
(b)

Figure 8.
Graphs relating to two exits of agent population 1,500 with 10 per cent rational agents and 25 per cent interactive agents across different strategies

Notes: (a) Utilization of left and right exits by agents; (b) agents' distribution across two exits evacuation time as compared to E2. Also, E2 has comparatively lower evacuation time when compared to E3. Hence, symmetrical environment is considered the best to reduce evacuation time. Observing the time across multiple strategies, it is evident from the graph that there is significant difference observed in E2 and E3 whereas E1 does not show significant change in simulation time across different strategies. There is a gradual decrease in time in E3 from strategy 1 to strategy 4+ due to increase in accuracy of information. Strategy 5 shows a negligible increase in time which is due to the involvement of human cognitive abilities (i.e. trust model). Furthermore, this in combination with the game applied in Strategy 6 leads to increased amount of time. But, allowing agents to change exits more than once as in Strategy 6+, gives best results comparatively. These changes are partially replicated in E1 and E2. In case of these environments, an increase in time has been observed in Strategy 4 as well.

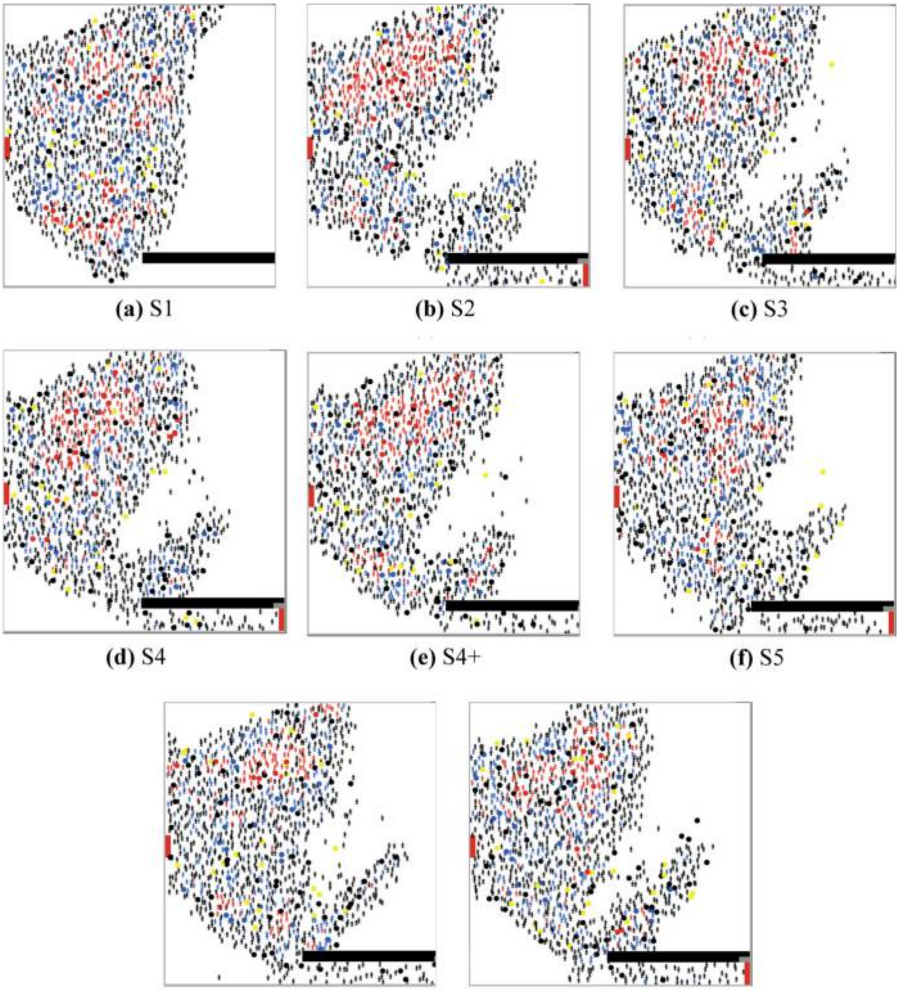
In Figure 12, two perspectives regarding agent distribution in relation to the exit points have been analyzed. Figure 12(a) shows the exit utilization percentage of the two exits, namely left and right. It is evident that E1 shows almost equal distribution of agents across the two exit points. In E2, more than half of the population chooses the exit on the left. This is mainly because of the asymmetric placement of exits. It was noted that E3 presents the most interesting results. Since the right exit is not visible to all agents, very few tend to exit from it, leaving most of the agents to exit from the left exit. Considering the right exit, there is a significant increase in the utilization of the right exit from Strategies 1 to 6, thereby reducing the congestion on the left exit to some extent.

In Figure 12(b), agents' distribution across the two exits has been illustrated in terms of iteration number (ticks). This graph shows the most recent iteration in which the left and right exits were used. In E1, no significant difference is observed in agents' distribution as agents are uniformly distributed across the two exit points. In E2, initially Strategy 1 shows a poor distribution of agents as it is based on nearest exit in asymmetric environment. But this difference has been minimized in Strategies 5 and 6+. The distribution is again unbalanced in Strategy 6, but this should be considered as undesirable though acceptable variation due to the involvement of human-centered behavior. Finally, in E3, there is a notable improvement in agents' distribution over time across the two exits. Strategy 6+ shows an almost equal distribution, proving to be the most effective strategy.



Notes: (a) Maximum number of agents in panic; (b) maximum Panic index value

Figure 9. Graphs relating to panic in agent population 1,500 with 10 per cent rational agents and 25 per cent interactive agents across different strategies



(a) S1 (b) S2 (c) S3 (d) S4 (e) S4+ (f) S5 (g) S6 (h) S6+

Notes: Ten per cent agents are rational represented by circles, whereas 25 per cent are interactive represented in yellow color. Rest of them are emotional agents. The agents in Blue are in waiting mode whereas agents in Red represent agents in Panic at 45th iteration

Figure 10.
The space with population of 1,500 agents in environment E3

Figure 13 analyzes the effect of herding during crowd evacuation. Figure 13(a) shows the number of agents in panic following different strategies in different environments. There is a gradual decrease in panic from E3 to E1 due to distribution of agents across the two exits. Hence, it can be concluded that an even distribution across the two exits can help to achieve lesser number of agents in panic. Looking at the effect of the different strategies on panic-stricken agents, a moderate decrease in panic is observed from Strategies 1 to 6+. However, there is a slight increase in panic in case of S5 in comparison to S4 due to

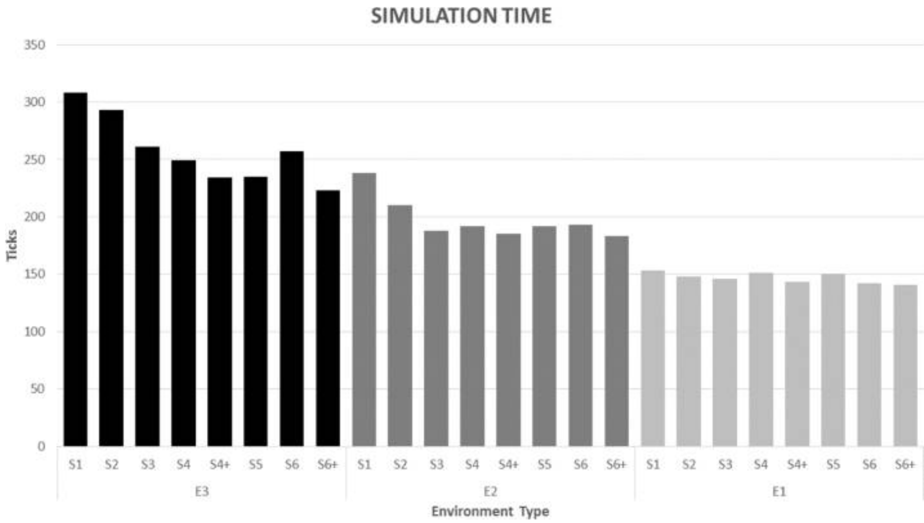


Figure 11. Simulation time across three environment settings

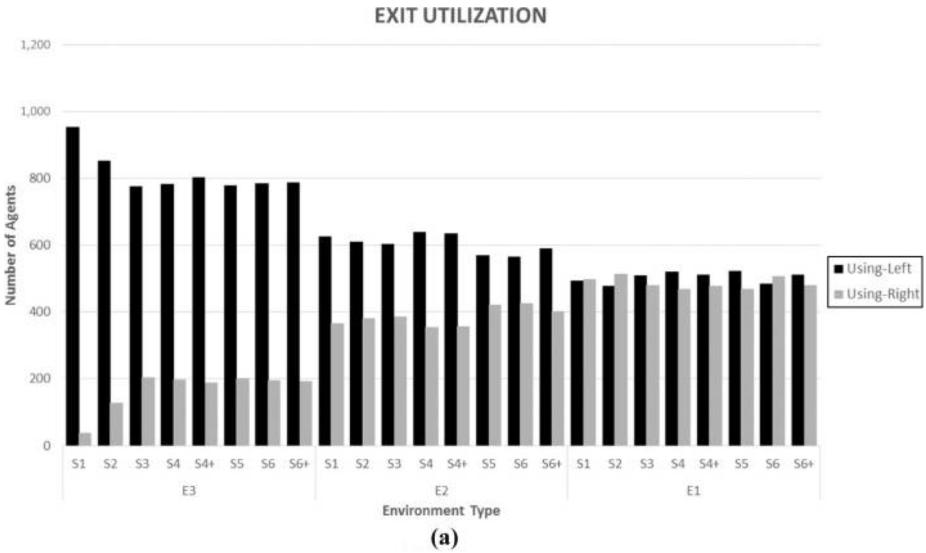
the trust factor. Trusting a wrong information source can result in increased number of panicked agents.

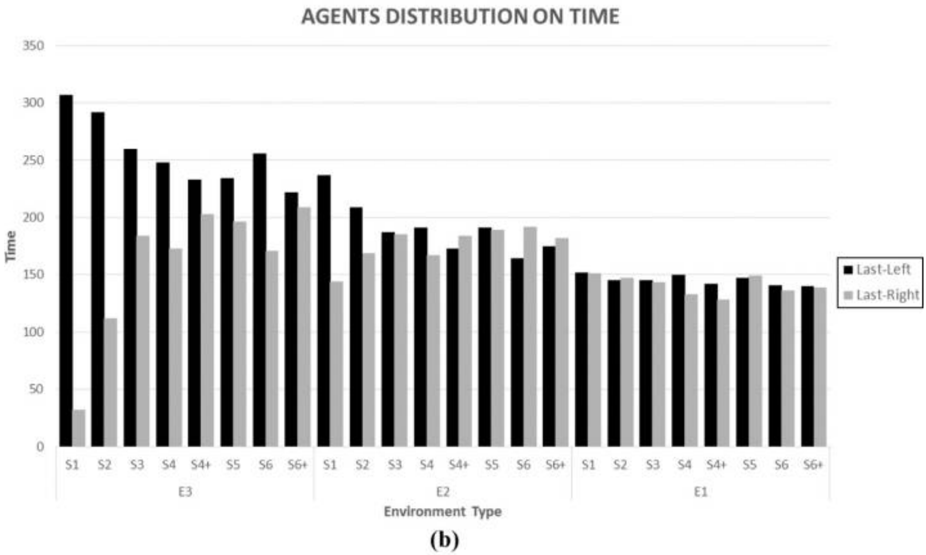
The graph in Figure 13(b) shows diverse results of the maximum PI value. This is mainly due to the agents' movement and how the evacuation scenario evolves as a consequence of different strategies. But, there is a consistent decrease in the PI value across environments E3 to E1. This is mainly due to agent distribution. One of interesting facts to observe is that the number of maximum agents in panic has no relation to the maximum PI value. For instance, in E2 & E3, Strategy 4+ shows a lower number of agents in panic as compared to S3 and S5, whereas the PI value is high in S4+ when compared to S3 and S5. The reason is that S4+ does not consider cognitive abilities and is solely based on interaction and neighboring decisions and thereby has a higher PI value.

5.4 Analyzing the ratio of emotional versus rational agents

To analyze the effect of the ratio of emotional vs rational agents' population on evacuation dynamics, a comparison between two sets of population of rational agents has been used. This scenario has been simulated on environment E2 with a total population of 1,000 agents. Having a large number of rational agents is unreal. Hence, percentage of rational agents has been analyzed for as low as 10 and 25 per cent of the total population. The percentage of interactive agents for each set of rational agents has been fixed at 50 per cent to compare results.

In Figure 14, a graph is plotted for each strategy against the two sets of rational agent population, i.e. 10 and 25 per cent, as shown along the horizontal axis. Here, it is clearly evident that an increase of agents exhibiting rational behavior results into a slight increase in evacuation time. But in two cases, S4 and S6, where the actual rational behavior is taken under consideration by playing the panic game, evacuation time is observed to decrease with the increase in rational agents. Contradictory to this, S4+ and S6+ show opposing results. The reason for this is simple. In these strategies, agents are allowed to switch exits more than once, so the greater the number of rational agents, the



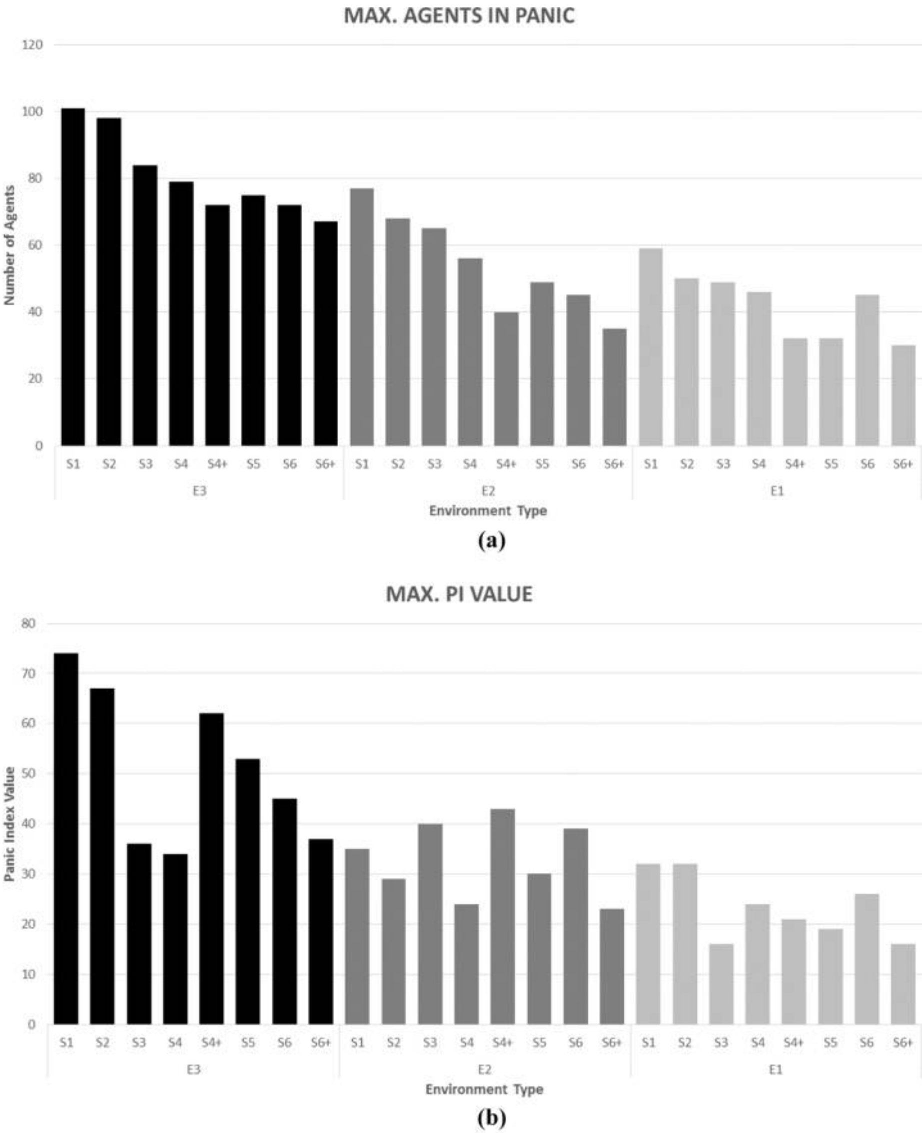


Notes: (a) Utilization of left and right exits by agents in three environment settings; (b) agents distribution across two exits in three environment settings

Figure 12. Graphs relating to two exits of agent population 1,000 with 10 per cent rational agents and 50 per cent interactive agents

more the population tends to switch exits with evolving conditions. Therefore, time taken to exit increases.

Observing the panic factor, Figure 15 shows the total number of agents in panic in varying populations of rational agents. It can be deduced that the more the percentage of



Notes: (a) Maximum number of agents in panic across three environment settings; (b) maximum Panic index Value across three environment settings

Figure 13. Graphs relating to panic in agent population 1,000 with 10 per cent rational agents and 50 per cent interactive agents

rational agents, the more the number of agents in panic state. The reason can be explained with a popular saying which states, *too many cooks spoil the broth*. This means that if there are more than a certain number of rational agents, it would leave a bad impact on emotional agents with diverse choices, thereby creating chaos leading to panic. In addition to this, in

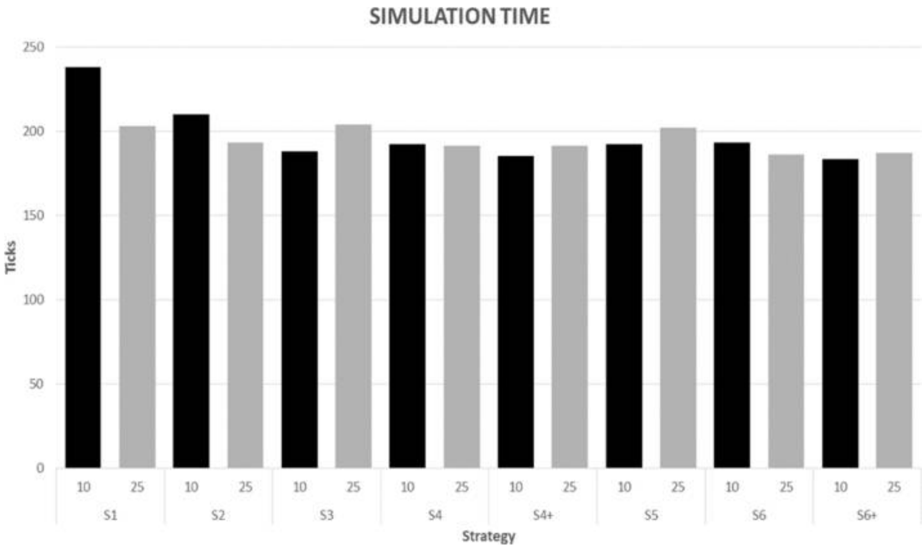


Figure 14.
Effect of rational agent population on evacuation time

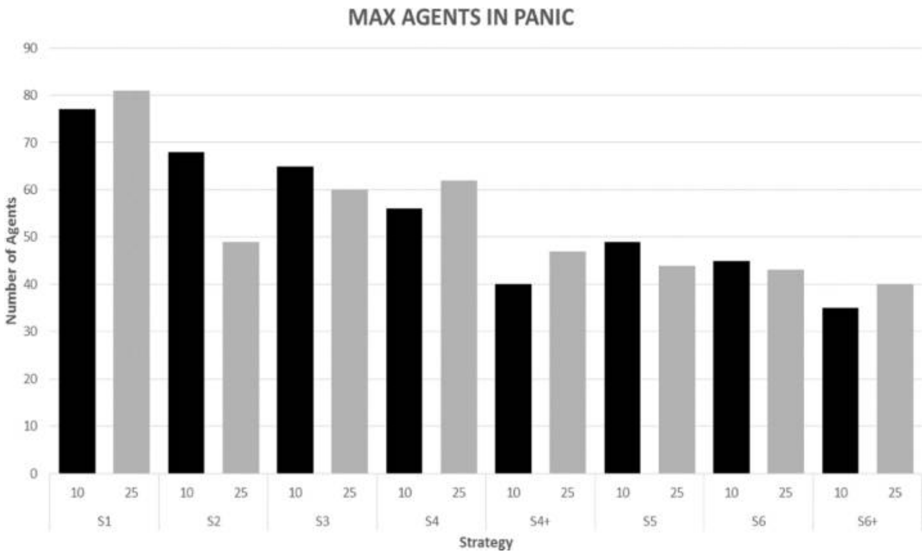


Figure 15.
Effect of rational agent population on number of agents in panic

strategy 6, contradictory results are observed. Here, panic-stricken agents become few with increase in rational agents, mainly due to the trust model. The trust model allows them to take decisions not solely on their neighbors' behavior, but also based on their personal observation.

Having a large population of interactive agents can help to achieve the desirable outcome of reducing evacuation time. In Figure 16, a comparison between two sets of interactive

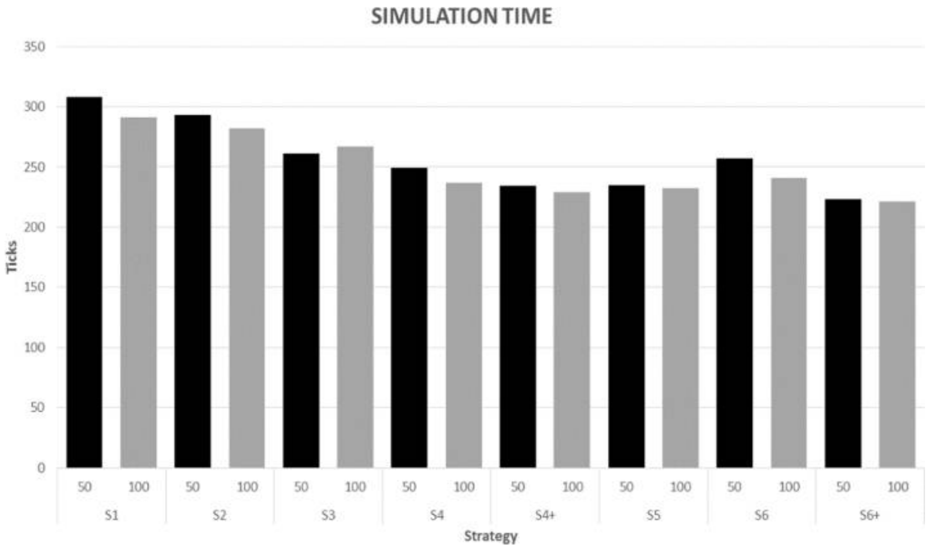


Figure 16.
Effect of interactive agents' population on evacuation time

agents has been shown, keeping the rest of the settings same for each case. The graph indicates a slight decrease in time with 100 per cent interactive agents as compared to 50 per cent, across all strategies. A small deviation is observed in case of S3 which is acceptable because it focuses on updating information regarding regions through interaction and having more interactive agents would require agents to communicate with more agents, thereby resulting in increased time.

It was observed that having a large set of rational agents would generally result in increased panic. However, increasing the number of interactive agents results in reduced amount of agents in a state of panic, as shown in Figure 17. This means that communication helps to establish a connection between agents, allowing them to rely on each other. This relation could benefit the agents by their cooperating with each other towards achieving the same goal. Furthermore, this reliance helps agents to avoid being in a state of panic. Although S2 shows some contradictory results, but as it does not involve interactive agents, it can be ignored.

6. Conclusion

To improve evacuation efficiency, in addition to the structural layout of the evacuation space, other factors such as agents' personal observations, cognitive abilities and communication with other agents play a major role. This paper formulated a model which integrates structural and cognitive features of decision-making. In this paper, multiple aspects that affect an evacuation scenario are studied using an agent-based simulation. The proposed model integrates the game theoretic approach of emotional and rational agents with the concept of perception map to reduce the effects of herding during evacuation. The perception map develops the spatial information based on densities of sectors. Using an information sharing model, agents can gain an overall view of the environment that is sufficient to select the optimal path toward the exits. Information sharing is governed by a trust model. In addition to this, competitive vs cooperative behaviors of emotional and

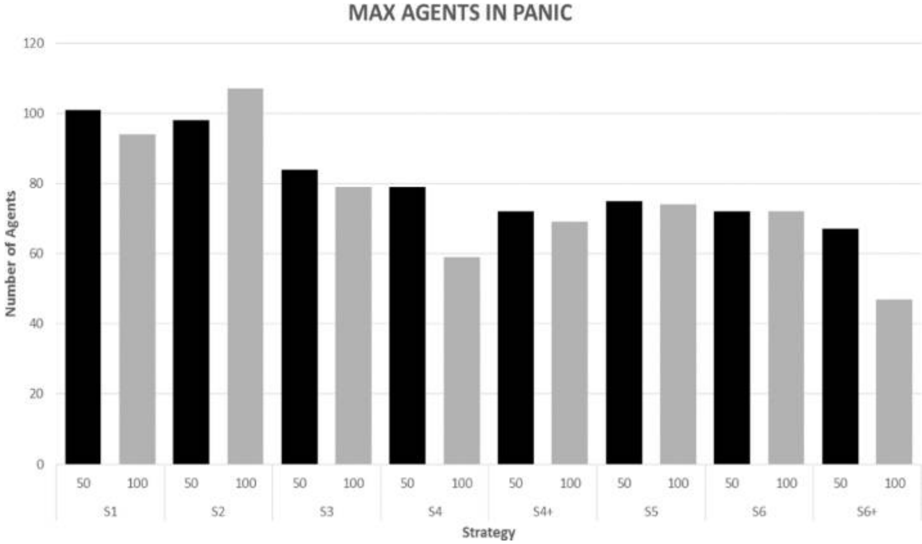


Figure 17.
Effect of interactive agent population on number of agents in panic

rational agents in an AmI environment are analyzed. For future work, the model can be extended to include spaces with multiple obstacles, environments with more than two exits and varying sizes of exits.

Notes

1. www.ndtv.com/photos/news/deadly-stampede-in-cambodia-over-300-dead-8646#photo-106736
2. http://america.aljazeera.com/articles/2015/10/19/hajj-disaster-death-toll-over-two-thousand.html

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