Original Paper

Adaptive Behavior

Adaptive Behavior
1–11

DOI: 10.1177/1059712316635719
adb.sagepub.com
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Quantifying the interplay of emotions and rationality in herding: A game-theoretic simulation study

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Abstract

In this paper, we apply game theory to analyze interplay between emotions and rationality, to reduce the effect of herding during evacuation. The simulation model developed for this work incorporates the social behavior of the crowd to ensure an improved evacuation. This model is simulated for four strategies, built upon both social and technological aspects of decision-making, with varied sets of the agents' density and type being either rational or emotional.

This work is evaluated both quantitatively and qualitatively using parameters such as simulation time, agents' distribution across exits, exit utilization, and panic. Mixed results were achieved in general; however, the game variation allowing more than one exit change showed an improvement over both variations of the game allowing a single exit change.

Keywords

Agent-based modeling, simulation, herding behavior, game theory, adaptive social behavior

1 Introduction

Herding during evacuation is a major reason of deaths in emergency situations. 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. This usually happens when the whole crowd adopts a single exit while leaving the others unused (Wang, Huang, Cheng, & Zheng, 2015). This results in asymmetric utilization of resources both in terms of exit usage and evacuation time. When a crowd starts using one exit, it creates more panic with time, due to congestion, rather than diffusing it (Helbing, Farkas, & Vicsek, 2000). Crowd behavior (including the herding effect) can be represented either at macroscopic or microscopic scale (Zheng, Zhong, & Liu, 2009). However, herding emerges due to local interactions between individuals (microscopic level), rather than being a global phenomenon of a crowd as a whole (macroscopic level) (Raafat, Chater, & Frith, 2009). Microscopic-level modeling can efficiently be achieved by agent- based modeling (ABM) (Gilbert, 2008).

Smart environments and cities (Batty et al., 2012) are becoming popular due to the influential impact of technology on our social lives. Scientists are actively engaged in exploring the question "what would the social behavior of a population be if the individuals are being influenced by technology?" in environments with ambient intelligence (AmI) (Mitleton-Kelly, 2013). Exploring the crowd behavior in such an environment during evacuation from a building or a city has gained significant importance (Mitleton-Kelly, Deschenaux, Maag, Fullerton, & Celikkaya, 2013). Minimizing the herding effect during crowd evacuation in these environments is an interesting and new problem. However, to avoid being part of a herd (a potential outcome of technological influence), decisions must be made by the individuals. This brings us to the problem of modeling crowd behavior. The well-known categories of microscopic models include those based on physical laws, biological inspiration, human-centric theories of cognition, psychology and neurology, and game-theoretic approaches. Game-theoretic models describing the individual decision-making integrated with agents' functionalities, among them, however, have produced interesting results (Lo, Huang,Wang, & Yuen, 2006).

Reynolds probably developed one of the earliest model of crowd behavior. Rules extracted from nature-

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inspired phenomena were used to implement flocking of agents called boids. The model used physical measures of cohesion, alignment and separation to maintain a flock-like group mobility. Couzin (2009) presented an excellent description of the relationship between individuals and group-level properties of animal groups. Further, efforts to describe collective behavior in animals such as ant colonies and slime mold (Altshuler et al., 2005; Kalogeiton, Papadopoulos, Georgilas, Sirakoulis, & Adamatzky, 2015) have also been made.

Helbing and Molnar (1995) developed the social force model of crowd mobility which is one of the most pronounced contributions based on physical laws. Social force models use Newton's laws of motion to describe social forces between individuals. The most common physical laws that have been investigated by various researchers are repulsive interaction, friction forces, dissipation and fluctuations. Models based on cellular automata (CA) are also based on physical laws. CA is an artificial intelligence approach to simulation modeling defined as mathematical idealizations of physical systems (Ferscha & Zia, 2009; Kirchner, Namazi, Nishinari, & Schadschneider, 2003). The space and time in CA are discrete and physical quantities and are assigned discrete values from a finite set. The most recent work in this domain can be found in Müller, Wohak, and Schadschneider (2014) and Crociani, Piazzoni, and Vizzari (2015). These mechanisms are based on physical laws and biologically inspired models, however, they are not flexible and do not use human individual factors in decision-making.

Crowd behavior is also modeled in terms of human traits drawn from psychological, neurological and cognitive theories (Lu, Luh, Marsh, Gifford, & Tucker, 2014). Some of these models are based on cognitive associations of agents with the neighborhood, and they are, therefore, called social cognitive models. Sharpanskykh and Zia (2011) modeled individual cognitive attributes such as fear, hope, belief, and trust to evaluate the possibility of emergence of mass panic during evacuation. However, these models are complex and are not very helpful in understanding the co-evolutionary dynamics of crowd behavior in terms of discrete quantitative measures.

Game theory is a comparatively new domain for modeling crowd dynamics compared with the well-established research domains of economics and sociology (Nowak, 2006), and therefore needs more attention (Zheng & Cheng, 2011a). Game-theoretic models are advantageous over the above-mentioned approaches as they provide mechanisms to handle the typical characteristics of the crowd dynamic. In particular, during evacuation, the behavior of individuals in a crowd continuously evolves over time, which may either lead to cooperative or to competitive behavior (Zheng & Cheng, 2011a). Models purely based on social force and CA are unable to handle such behavioral changes of individuals. Similarly, models based on human psychology or animal instincts are tightly bound with cognitive and neurological principles. However, they are not flexible enough to ask all the interesting "what if" questions. Many game-theoretic approaches such as those presented in Zheng and Cheng (2011b), Wang et al. (2015), Tanimoto, Hagishima, and Tanaka (2010), and Fu, Shi, and Wang (2015) modeled crowd dynamics during evacuation. However, to our knowledge, none of the existing models has used the AmI of an environment as a parameter in game strategy. This paper intends to fill this gap and the purpose of this work is to enhance evacuation efficiency by reducing the herding effect to achieve symmetric utilization of resources in terms of exit usage and evacuation time.

The following sections provide the background work and the motivation behind the model proposed in this work. They present the proposed model and provide evaluation results, followed by the conclusion of this work.

2 Related work

Game-theoretic models have been developed for usual problems of crowd dynamics during evacuation. Lo et al. (2006) presented a game-theoretic model for exit selection during crowd evacuation. Similarly, Tanimoto et al. (2010) presented a decision-making model for crowd flow at bottlenecks. However, Zheng and Cheng (2011a) claim the development of the first ever game-theoretic microscopic-level framework for evacuation. They used CA which is capable of resolving conflicts between agents. They investigated the impact of playing the conflict game based on factors such as rationality, the herding effect and conflict cost on parameters such as evacuation time and strategy switch. This framework was used to study the problem of realizing circumstances of phase transition of cooperative and competitive evacuees and its effect on evacuation time (Zheng & Cheng, 2011b).

Our work is inspired by the recent work of Wang et al. (2015). They presented a co-evolutionary model of strategy and game structure to understand the herding effect on an evacuating crowd. The population used in their simulations was divided into two subpopulations based on individuals being either emotional or rational. Each individual in the emotional subpopulation tends to select the same behavior as most of the other individuals nearby. However, each individual in the rational subpopulation tends to select a different type of behavior than most of the other individuals nearby. They developed a simple two-player game and carefully set appropriate payoffs to get the desired results by considering only the observed behavior of neighboring agents. With the help of this simple game, the authors studied different phenomena such as extinction of one subpopulation and the herding effect.

However, we believe that it is probably irrational that an agent will be "rational" if it makes a decision contrary to the decision taken by most of the individuals in its range of influence. If an agent is smoothly moving towards a desired exit, why should it deviate from its course of action? For example, if an agent has observed that an exit is the nearest and the agent is moving at a satisfactory pace towards that exit, it seems inappropriate to deviate the agent from the path towards that exit just because it is rational. The definition of "agent" in this work is not humanistic in nature, and needs replacement with a more knowledgeable agent that acquires knowledge from its previous experiences, beliefs, and/or observations.

In this paper, we propose a more realistic model that provides an initial exit, most probably the nearest one. If an agent is productively covering the route towards an exit, no deviation takes place. However, as it faces difficulty in doing so, it allows switching of the exit. This difficulty is termed "panic" in this work. The proposed model uses the ABM technique and it is flexible enough to answer various "what if" questions. It has the potential to track the behavior of agents at an individual level. We provide a more robust environment and it allows testing behavior against various distributions of the population and different types of environments. Further, our model incorporates a sensitivity measure to develop an AmI scenario. It is believed that a rational agent, if provided with directional technological guidance, will always adhere to it. For this reason, in this work, we will send directional guidance to a subset of agents based on the sensitivity measure. The basic aim is to avoid phase traditions in a loop for improved evacuation.

3 The proposed model

3.1 Space description

This work uses a two-dimensional square-shaped space comprised of cells of equal sizes for evaluation purposes. The space is represented as a grid of cells. The conversion of the space into a grid of cells provides an easy way to manage the occupancy and mobility of agents. Many agent-based integrated modeling environments such as NetLogo (Wilensky, 2015), Repast (Collier & North, 2011), Mason (Luke, Cioffi-Revilla, Panait, Sullivan, & Balan, 2005) and Swarm (Minar, Burkhart, Langton, & Askenazi, 1996) represent the spaces they use in the form of grids of cells. Mobile agents reside on top of the cells and they are capable of using the information of desired neighboring cells (agents) to make their decisions. These environments provide fair chances of selection to the agents based on randomness.

The square space adopted has two exits. Cells in the grid are enriched with the floor field that contains the nearest exit distance and direction at cell level before populating the space with agents. This information is used by the agents to make decisions about moving towards the desired exit. Figure 1 presents three cases of exit distribution based on the nearest exit measure. These distributions are called symmetric, asymmetric and hidden. The initial exit measure (the nearest exit) act as the initial belief of the agents while routing towards an exit.

3.2 Agent population

The following three cases are used for random distribution of agents before starting a simulation.

1. Sparse: 500 agents with a density of 0.2 per cell.
2. Medium: 1000 agents with a density of 0.4 per cell.
3. Dense: 1500 agents with a density of 0.6 per cell.

Rational agents in each case are 0%, 10%, 20%, and 30% of the overall population. The rest of them are emotional.

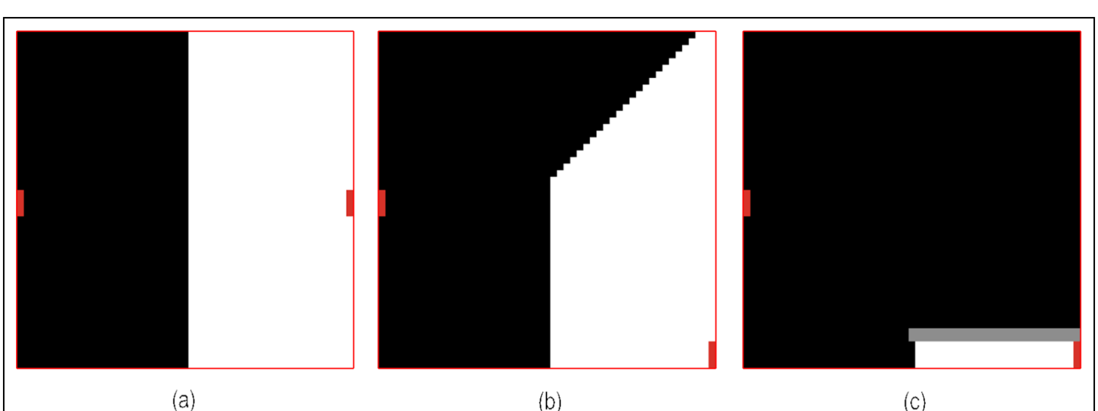

Figure 1. Three geometric variations of two exits shown in red. (a) Symmetric: the number of cells closer to the left exit (shown in black) is equal to the number of cells closer to the right exit (shown in white). (b) Asymmetric: the number of cells closer to the left exit (shown in black) is not equal 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).

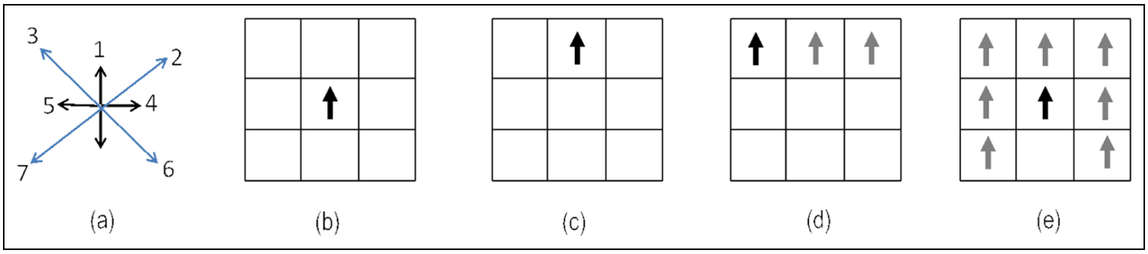

Figure 2. The next cell selection strategy explained. (a) Directional preferences of an agent with intended direction labeled '1'. (b to c) Move of agent at the center to the unoccupied cell in intended direction. (b to d) Move of agent at the center to the unoccupied cell NOT in intended direction and 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.

Table 1. The base game: A variation of Wang's game explained (Wang et al., 2015).

Player 1 (Agent)	**Player 2 (Random Neighbor)**			
	Emotional		**Rational**	
	Behavior 1	Behavior 2	Behavior 1	Behavior 2
Behavior 1	1	1*	0**	1
Behavior 2	1*	1	1	0**

*Exit change with probability 0.1, if PI>0; **exit change with probability 0.9.

3.3 Next cell selection criteria

The next cell selection strategy adopted in this work is based on the concept of Moore's neighborhood (Kretz & Schreckenberg, 2005). In this strategy, an agent can choose one of its eight neighboring cells depending on the direction in which it is traveling. However, it uses the strategy shown in Figure 2 to choose the desired cell, which may already be occupied by another agent. In this case, the agent adopts a strategy to choose an unoccupied cell, if the desired cell is already occupied. Figure 2(a) shows a dial towards the intended direction labeled "1". If the cell in this direction is occupied, the agent will choose the direction labeled "2", and so on. The strategy is based on empirical evidence explained by Ferscha and Zia. Further detail on this is beyond the scope of this paper and interested readers may see details in Ferscha and Zia (2009).

The following state variables are used to record the locomotive behavior of the agents.

1. The mobility index (MI) is an incremental index recording continuous mobility of an agent. If an agent intends to move to the cell in the "up" direction, and the desired cell is not occupied as in Figure 2(b), then after the move (see Figure 2(c)), the MI value will be one more than the value in the previous iteration. If an optimal move is not possible, as in Figure 2(d), but an agent is able to move in the up–left or up–right direction, the MI value is incremented. When the value of MI is incremented, the two indices described below are reset to 0.
2. The waiting index (WI) is an incremental index recording the continuous state of an agent not able to make a move. The agent in Figure 2(e) is not able to make a move according to the preferences given in Figure 2(a). This is because all seven neighboring cells are already occupied. The current WI value in this case is incremented by 1 while resetting the MI value to 0.
3. The panic index (PI) records the agent being in a state of panic for a continuous sequence of iterations. The WI value is used to set an agent in the "panicking" state if WI crosses a threshold value. The WI and PI variables are reset to 0 when an agent starts moving again.

The next cell selection mechanism is initiated when an agent knows the direction to move under the influence of one of the strategies presented next.

3.4 Exit strategies

3.4.1 Nearest exit: Strategy 1 (S1). The agents in all strategies proposed in this work are assumed to start with the nearest visible exit. This strategy is used to compare it with game-theoretic approaches allowing switching of exits.

3.4.2 The base game: Strategy 2 (S2). It is a variation of Wang's game (Wang et al., 2015) and it is explained in Table 1. Player 1 (termed "agent") is the one who is making a decision, and Player 2 (a random neighbor from Moore's neighborhood) is the influencer.

For an emotional agent, if the behavior of the neighbor is same as its own behavior, then the payoff is maximal and the agent retains its behavior, which is keeping moving towards the current exit. The payoff remains maximal when the behavior of the random neighbor is the opposite of the agent's behavior. However, there is a 10% chance that an agent may change its behavior if PI > 0 which ensures random deviation. This means that the game is not really played by emotional agents. It is the rational agent who plays the game (a precondition when adopting a game theory for modeling).

For a rational agent, the game is kept same as Wang's game (Wang et al., 2015). Minimal payoff/gain is achieved for the same behavior suggesting the agent should change its behavior with a 90% probability thus again ensuring random deviation. In this case, the agent being in a panic or not in a panic has no impact on the payoff. This strategy allows only a single exit change to avoid endless phase transitions. A rational agent strictly retains its recent behavior, if the neighbor's behavior is different from its own behavior.

3.4.3 The panic game: Strategy 3 (S3). This game uses the same strategy as the base game for emotional agents. However, the strategy for a rational agent is now dependent on whether it is in a state of panic or not. The panic game is explained in Table 2.

If the agent is not in a state of panic, if the random neighbor has the same behavior this will be a source of strengthening of its belief about its current behavior. This represent the maximum payoff in this case. On the other hand, if the random neighbor has the opposite behavior, this will be a source of weakening of its belief about its current behavior. This represents the minimum payoff in this case. However, there is a 90% chance that the agent will change its behavior, leaving a 10% chance of random deviation.

If the agent is in a state of panic, it behaves like the base case in which same behavior represents minimum payoff. This directs the agent to change its behavior, but strictly this time. Similarly, if the behavior of the random neighbor is different from agent's own behavior, the agent will strictly retain its recent behavior.

3.4.4 The extended panic game: Strategy 4 (S4). It is different from the panic game only in terms of the provision of more than one exit change if the rational agent is in a state of panic. The exit changes for an emotional agent, however, can only happen once in the lifetime of the agent to avoid endless phase transitions.

The rational agent follows the base game (S2) exactly, before the first exit change. However, the agent may perform a second exit change but based on

Table 2. The panic game explained.

Player 1 (Agent)	**Player 2 (Random Neighbor)**					
	Emotional		**Rational**			
			Not in Panic		**In Panic**	
	Behavior 1	Behavior 2	Behavior 1	Behavior 2	Behavior 1	Behavior 2
Behavior 1	1	1*	1**	0***	0	1
Behavior 2	1*	1	0***	1**	1	0

*Exit change with probability 0.1, if PI>0; **exit change with probability 0.1; ***exit change with probability 0.9.

Table 3. The extended panic game explained.

Player 1 (Agent)	**Player 2 (Random Neighbor)**					
	Emotional		**Rational**			
			Not in Panic		**In Panic**	
	Behavior 1	Behavior 2	Behavior 1	Behavior 2	Behavior 1	Behavior 2
Behavior 1	1	1*	1**	0***	0	1, Sensitivity
Behavior 2	1*	1	0***	1**	1, Sensitivity	0

*Exit change with probability 0.1, if PI>0; **exit change with probability 0.1; ***exit change with probability 0.9; sensitivity = {0.2,0.4,0.6,0.8}.

Table 4. Test cases for all possible scenarios based on (environment[symmetric/asymmetric/hidden], density[sparse/medium/dense]) combinations.

Strategy	Sensitivity	Rational (%)
S1	Not applicable	Not applicable
S2	Not applicable	10
S2	Not applicable	20
S2	Not applicable	30
S3	Not applicable	10
S3	Not applicable	20
S3	Not applicable	30
S4	0.2	10
S4	0.2	20
S4	0.2	30
S4	0.4	10
S4	0.4	20
S4	0.4	30
S4	0.6	10
S4	0.6	20
S4	0.6	30
S4	0.8	10
S4	0.8	20
S4	0.8	30

probability values (termed as sensitivity) assigned to a particular case. Four different cases are defined based on 20%, 40%, 60%, and 80% probabilities. The introduction of sensitivity helps us develop a scenario based on AmI. Based on the environment type and population dynamics, we can send directional guidance to a specified percentage of agents to achieve improved performance. The structure of this game is presented in Table 3.

4 Evaluation/simulation

4.1 Experimental setup

Netlogo (Wilensky, 2015) is used for the evaluation of the proposed model. It uses a 50×50 grid of cells to represent a world. This work uses the three different exit settings (termed symmetric, asymmetric and hidden) shown in Figure 1. Each of these exit possibilities is simulated with three possible densities of the agents' population (sparse, medium and dense) which correspond to spatial dimensions of the simulated world. Each combination of exit settings (environment) and agents' density is simulated for the set of test cases presented in Table 4. These combinations provide a number of scenarios that are named symmetric sparse (SS), symmetric medium (SM), symmetric dense (SD), asymmetric sparse (AS), asymmetric medium (AM), asymmetric dense (AD), hidden sparse (HS), hidden medium (HM), and hidden dense (HD).

Each test case describes the sensitivity level and percentage of rational agents. Each strategy except S1 is evaluated for 10%, 20%, and 30% rational agents. S4 uses an additional parameter called sensitivity in decision-making which takes its value from a set of values comprised of 0.2, 0.4, 0.6, and 0.8. Without considering the sensitivity, S4 is same as S3. Each test case was simulated 10 times with a different set of agents randomly distributed during initialization, and then the average values were obtained and used for comparison in this work.

4.2 Experimental results

The proposed model is evaluated with both quantitative and qualitative measures. The following two parameters are used for quantitative analysis.

1. Case simulation iterations (CSI): the number of iterations required to complete simulation of a test case.
2. Agents' distribution: relative number of agents exiting through two possible exits named "left" and "right".

The following parameters are used for qualitative analysis.

1. Exit activity: for how long (in terms of iterations) an exit has been used before the simulation ends.
2. Difficulty level: the number of agents in a state of panic (having PI greater than or equal to 1).

Each of the scenarios discussed earlier is tested for all test cases presented in Table 4. There is no distinction between rational and emotional agents in S1. S2, S3, and S4 are tested for the populations with a subset of 10%, 20%, or 30% rational agents. S4 is additionally tested for different sensitivity levels (0.2, 0.4, 0.6, and 0.8) for each population sub-divided into rational and emotional.

In S1, all the agents always exit through the nearest exit and Table 5 shows that the CSI value increases in a linear fashion for a single environment type with an increase in density. For symmetric exits, it increases from 87 (for 500 agents) to 163 (for 1000 agents), which is an increase of 87%, and then to 229 (for 1500 agents), an increase of almost the same quantity. However, there is a slight increase in more challenging environment types (which is understandable). The difference, for example, between CSI in the case of the sparse agent population, from the symmetric to the asymmetric environment is 32%, and going from the asymmetric to the hidden environment, it is 42%. Again, there is a slight increase in these differences for medium to dense populations, but the trend remains the same.

Taking S1 as the base case, we focus on comparing the effectiveness of all the strategies. The proposed strategies for the symmetric environments can be organized into the following three categories based on the differences between CSI values.

Table 5. Results of quantitative evaluation: simulation time and agents' distribution.

Strategy	Scenario	**Simulation Results**			Scenario	**Simulation Results**			Scenario	**Simulation Results**		
			Agents' Distribution				**Agents' Distribution**				**Agents' Distribution**	
		CSI (Num)	Left (Num)	Right (Num)		CSI (Num)	Left (Num)	Right (Num)		CSI (Num)	Left (Num)	Right (Num)
S1	Symmetric sparse	87	253	247	Asymmetric sparse	115	304	196	Hidden sparse	163	482	18
S2		102	253	247		125	284	216		171	393	107
S3		104	254	246		122	284	217		175	393	107
S4(0.2)		105	249	251		126	285	215		173	394	106
S4(0.4)		106	253	247		127	285	215		174	394	106
S4(0.6)		107	254	246		127	281	219		174	394	106
S4(0.8)		107	254	246		126	283	217		172	394	106
S1	Symmetric medium	163	511	489	Asymmetric medium	215	613	387	Hidden medium	308	966	34
S2		163	503	498		202	561	439		312	745	255
S3		167	509	491		206	560	440		318	747	253
S4(0.2)		180	504	496		205	580	420		299	785	215
S4(0.4)		177	503	497		204	577	423		293	788	212
S4(0.6)		180	506	494		204	578	422		293	787	213
S4(0.8)		177	513	187		205	580	420		297	784	216
S1	Symmetric dense	229	759	741	Asymmetric dense	307	922	578	Hidden dense	455	1449	51
S2		229	753	747		299	829	671		543	976	524
S3		230	751	749		294	825	675		543	979	522
S4(0.2)		241	756	744		289	862	638		454	1136	364
S4(0.4)		247	755	745		288	870	630		450	1144	356
S4(0.6)		247	757	743		285	869	631		448	1139	361
S4(0.8)		243	756	744		286	874	626		455	1143	357

1. S1: has the smallest CSI value.
2. S2 and S3: the difference between these two strategies is negligible; their difference from S1 is 18% in the sparse population, and their difference from S1 is 1–2% in the medium and dense populations.
3. S4 (with all variations): the difference of the S4 strategies from S1 is below 10% and can be considered uniform.

The only aberration appears in the SS scenario in which the CSI value in the case of S1 is too small. However, this can be ignored as a special case due to sparse agent density.

The above pattern also persists in asymmetric and hidden environments, but only for the sparse population. In the AM and AD scenarios, we observe an opposite trend in which S1 takes more simulation time than other strategies, whereas the difference between S2, S3, and S4 is negligible. These cases present the effectiveness of S2 over S1. The reason for S1 taking more iterations when compared with S2 is the unequal agent distribution which balances out from 61%–39% (left–right) in the case of S1 to 56%–44% (left–right) in the case of S2 (see Table 5). This hints that Wang's original game is expected to underperform when compared to S1 even, due to the potential of shifting most agents from left to right. This would result in more imbalance in the left–right agents distribution. As a result, the CSI value will be more than S1 due to more agents moving towards the exit which is not nearest.

The HM and HD scenarios presented the most interesting results. In the case of S1, both cases end with the agent distribution of 97%–3% (left–right). This changes in the case of S2 and S3 to 75%–25% (left–right) in the medium population and 65%–35% (left–right) in the dense population. Later in the case of S4, the distribution changes to 79%–21% (left–right) and 76%–24% (left–right) respectively, increasing when compared with S2 and S3 in both cases. Hence, the geometry of the space plays a crucial role in defining how a strategy would distribute the agents. Although these two scenarios generated non-uniform results, they depict the usefulness of S4 when compared with S2 and S3, bringing the CSI value closer to the CSI value of S1.

The strategies were not explicitly designed to distribute agents evenly between two exits (because of pure microscopic interaction), but still some strategies worked better than the others. Similarly, the simulation environment represented three generic geometries, and the actual environment can be far more complex than these, but we can still relate all analyzed aspects in a meaningful way. For example, the non-uniformity in the HM and HD scenarios, starting from an acute imbalance (in the case of S1), to an increase in distribution balance (in the case of S2 and S3), finally culminates in a decrease in distribution balance (in the case of S4). This brings the SS value closer to S1, and even less than S1 in some cases.

Exit activity also supports this improvement in terms of CSI value. Even though there is not much difference in last exit usage (in terms of iterations) of the left and right exits in other cases, for the HM and HD scenarios it is different. The difference in when the left and right exits were used last between S1 and S2, S3 is 15% in the case of the medium and 20% in the case of the dense population. However, S4 reduced these differences to 8% and 12%, respectively. Detailed results on this are not included due to similarity with the earlier results. A comparison can be made exclusively from agents' distribution and exit activity for all the cases and their obvious influence on the CSI value can be established.

Finally, we analyze the panic in the system using Figure 3. There is a decrease in the maximum panic index from S1 to other strategies. Generally, the panic index decreases from S2 to S3 to S4. Within S4, it varies.

4.3 Discussion

There is no particular trend within S4 in all quantitative and qualitative aspects. However, overall, some variation of S4 is always better than S2 and S3. It would be the subject of future work to insert more realistic environmental maps into the simulation to decide on the best variation of S4 for a given map. However, if it is not possible to change the exit option more than once, either S2 or S3 can be used.

While leaving the difference in the results (not shown here) due to the percentage of rational agents being 10%, 20%, and 30% aside, the average values of the evaluated aspects are similar in panic and the base game. It is an interesting finding that there is no significant difference between S2 and S3. In simpler words, the panic game, although more sophisticated in terms of fulfilling the psychological factors related to the scenario, transforms into its simpler counterpart (the base game). The following are the two major factors contributing towards this.

1. The percentage of rational agents is always smaller than that of emotional agents, thus overriding any marked effect generated by rational agents. However, this assumption is taken from real life, in which rationality is a meager commodity, particularly in panic situations.
2. Discreteness in panic updates: an agent practically forgets that it is in a panic state, as soon as it starts moving again. So most of the agents would be in a state of panic once in their lifetime, without accumulating any effect for the future. A more realistic psychological model will not only avoid setting the panic index to 0 when an agent is exiting from the panic state, but will also cater for uneasiness in

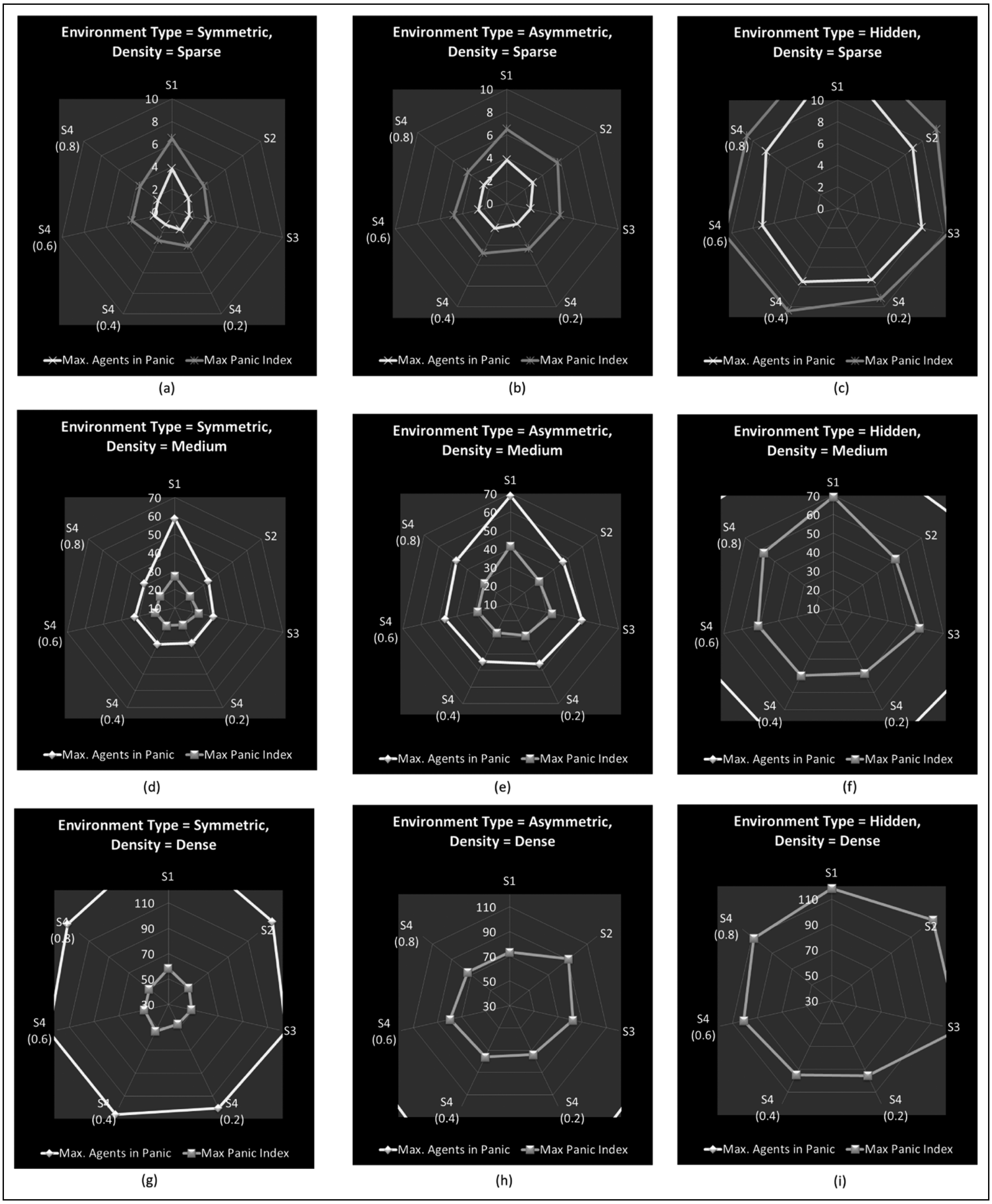

Figure 3. Qualitative simulation results: a comparison of panic of scenarios and their corresponding test cases, represented as [Environment Type, Density] combination and instanced as (a) Symmetric, Sparse, (b) Asymmetric Sparse, (c) Hidden, Sparse (d) Symmetric, Medium, (e) Asymmetric Medium, (f) Hidden, Medium, (g) Symmetric, Dense, (h) Asymmetric Dense, and (i) Hidden, Dense.

the agent's behavior escalating with its repeatedly transiting into the panic state. However, introducing such a model is not a focus of this research.

Hence, in the absence of a more realistic agent behavioral model, we can ignore S3 and contend with S2. S3 will still be relevant as a starting game for S4, which turned out to be the best strategy overall.

5 Conclusion

The overall purpose of our research is to enhance the evacuation efficiency by reducing the herding effect, resulting in symmetric utilization of resources in terms of exit usage and evacuation time. For reasonably varied environment types, four strategies of increasing variations were used, built upon social as well as technological aspects of decision-making, and simulated in different settings of agents' density and type. It was observed that in the absence of a more representative panic behavioral model, the panic game is comparable with the base game. The extended panic game turned out to be the best overall strategy. However, the best variation of the extended panic game corresponds to the sensitivity level, which can only be realized in the presence of a moderating outside influence, for example a recommendation provided through technology in the environment. Moreover, there is no particular trend within the extended panic game in all quantitative and qualitative aspects. However, overall, some variation of it is always better than the other two games. Including more realistic environmental maps in the simulation to decide on the best variation of the extended panic game for a given map is part of our future work. The extended panic game also ignores the potential resistance of human beings to repeated behavioral changes. This can again be triggered through technology-based recommendation which is expected to decrease this resistance. However, this needs to be modeled and tested, and remains future work.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

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