Modelling emergent pedestrian evacuation behaviors from intelligent, game-playing agents

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Abstract:

Much work has been done to understand complex crowd dynamics and self-organizing behaviors in high-density crowd situations. But most approaches for modelling pedestrian dynamics in emergencies require complex computations, making it difficult to capture multiple individual behaviors within a single model. This paper describes an agent-based model (ABM) that incorporates Bayesian game theory into pedestrian simulations. It assumes that players (agents) are playing a Bayesian game (i.e. games with incomplete information) and adopt strategies based on the anticipated behaviors of others to achieve a Bayesian Nash Equilibrium (BNE). Here, the model agents make decisions based on the possible positions of neighbors in the next time period to maximize their comfort and efficiently achieve their evacuation goal. A series of simulation experiments were undertaken using corridors, bottlenecks, and intersections in simulated evacuation spaces with the characteristics of mass tramping accidents. BNE provides a realistic and efficient approach for modelling complicated pedestrian dynamics with strong applicability. The BNE-informed ABM performance (evacuation times, routes, and behaviors) demonstrates its ability to realistically simulate emergent patterns of evacuation behaviors. The results indicate that agents using game theory reflect the behaviors of individuals with crowds well: BNE agents evacuate effectively at low densities and low blockages but are confounded in situations with few route choices in highly constricted spaces. The BNE-informed model provides a platform to better understand diverse crowd behaviors (e.g. herding and self-organized queuing, etc.) in varied spatial contexts, contributing to the designs of urban public space, evacuation planning, and crowd management.

Keywords:

Agent-based model, Bayesian Nash Equilibrium, Bayesian game theory, evacuation simulation, crowd simulation, pedestrian behaviors.

Statements and Declarations:

The authors have no competing interests to declare that are relevant to the content of this article.

Main Text:

1 Introduction

High-density and constricted public spaces (e.g. cinemas, shopping centers, etc.) can be a potential safety hazard to the public especially in situations such as mass gatherings during festivals, possibly leading to serious trampling accidents [1, 2]. Therefore, it is important to understand how pedestrians behave under these life-threatening situations. Many efforts have been made to incorporate game theory into behavioral and other elements in social sciences, resulting in various game-theoretic models for crowd evacuation [3-7]. It has been shown that integrating multiple crowd evacuation models (e.g. game-theoretical models, social force models, and agent-based models, etc.) can contribute to better reproduction of pedestrian movement under real-world scenarios [6, 8]. A number of microscopic simulation models have attempted to convert real-world interactions into games to further explore individual decision-makings. However, most focus mainly on exit route choice or routing network optimization rather than concentrating on the diverse escaping responses at an individual level [9-13]. Few studies have sought to model pedestrian behaviors in detail in a complicated space through game-theoretic and agent-based modelling approaches. One of the main obstacles is that complex computations are required for both individual response and different types of game-playing. Identifying an appropriate game structure and employing it in pedestrian simulations also require considerable thought.

Discovering a realistic description of complicated pedestrian behaviors in dense constricted urban space is a crucial issue that needs to be handled. Many studies have been conducted to derive underlying laws of human crowd dynamics, proposing that complex pedestrian behaviors are driven by both environmental constraints and social interactions among individuals [14]. Individual-level models for crowd simulation have then been developed to capture pedestrian behaviors at an agent level [15-19]. They reflect that most people in a crowd tend to move in groups rather than walking alone [20, 21]. Some of these pedestrian simulation models adopting physics-based approaches (e.g. social force models, etc.) can also be applied to simulating crowd behaviors in high-density situations, considering both external influences and local interactions among individuals to provide relatively satisfactory observations [7, 16, 22-24]. Many evacuation simulation studies mainly focus on a certain type of emergent phenomenon such as herding, etc. caused by social interactions and public emotions (e.g. panic), making it increasingly difficult to realistically capture multiple individual behaviors in a single model [10, 19, 24, 25]. Some relevant studies have conducted large-scale crowd evacuation modelling using agent-based models to explore the main elements influencing evacuation process in extreme social events (e.g. music festivals, concert venues, etc.) [2, 26, 27]. However, they rarely consider understanding complex crowd dynamics from the perspective of individual strategy-taking and game-playing in life-threatening situations involving different types and degrees of strategizing.

This paper develops an agent-based model (ABM) building upon the findings of the existing research conducted by Wang et al. [28] and incorporating Bayesian game theory into pedestrian simulation to reproduce emergent behaviors of pedestrians in varying high-density and life-threatening situations. It is based on the assumption that intelligent agents participate in Bayesian games (i.e. games with incomplete information) and strive to achieve a Bayesian Nash Equilibrium (BNE) in which players take the strategy considered to be the best responses to each other [29]. BNE was adopted to describe the interactive decision-making process among intelligent and game-playing agents, since its application context relaxes complete information constraints and adopts incomplete information assumption [28]. An underlying BNE-informed model was therefore developed to simulate emergent patterns of individual evacuating behaviors so as to provide a more realistic description of complicated pedestrian dynamics especially in high-density and life-threatening situations. Relevant studies [30,31] indicate that serious incidents caused by mass crowds (e.g. Seoul Halloween crowd crush shown in Fig. 1) and dense spaces with potential risk of stampedes (e.g. Oxford Circus metro station in London, Fig.2) generally have several common characteristics: 1) they all took place in extremely constricted space (e.g. narrow alley) with large crowds; 2) the spaces all had bad bottlenecks with clogging effects; and 3) there are body collisions in intersecting flows. On this basis, this paper performs a series of simulation experiments using varied corridors, bottlenecks, and intersections to investigate the emergent patterns of human evacuating behaviors (e.g. herding and leader behaviors, etc.) with intelligent BNE agents in varying constricted spatial environments.

Figure 1 The narrow alley where the deadly crush happened during a Halloween event in Seoul's Itaewon district on 29 Oct 2022. [1]

Figure 2 Crowd gatherings at an entrance to Oxford Circus metro station in London.[2]

[1] Retrieved from https://www.theguardian.com/world/2022/oct/31/how-did-the-seoul-itaewon-halloween-crowd-crush-happen-unfolded-a-visual-guide

[2] Retrieved from https://www.dailymail.co.uk/news/article-3186134/Tube-strike-begins-London-commuters-pack-Underground-trains.html

2 Methods

This research develops an agent-based model (ABM) that introduces Bayesian game theory to simulate pedestrian evacuation behaviors during emergent situations in varying urban spaces. Bayesian Nash Equilibrium (BNE) has therefore been incorporated to describe the interactive decision-making process among intelligent, game-playing agents. This BNE-informed ABM builds on a previous study conducted in 2023 [28], and three types of individual behavioral models (i.e. Shortest Route (SR), Random Follow (RF), and BNE models) have been implemented to better model people's emergent evacuating behaviors in different spaces from an individual level. The SR behavioral model employs Dijkstra's searching algorithm to reproduce the shortest pathfinding strategy. All SR agents know their final goal from the beginning of each simulation and strive to evacuate through the shortest route to the exit while avoiding the barriers on the way. RF behavioral model was implemented to simulate the leader behavior often occurring in emergent situations. Among them, 20% of the total are set as the leaders who intend to follow the shortest route to evacuate, and the remaining agents (i.e. followers) randomly select a leader in view to follow, inclined to gather around the nearest one to them. The BNE agents have clarity on their final destination from the beginning and intend to find an evacuation route with shorter exit time and higher comfort level. The following section mainly focuses on the improvement details of the BNE behavioral model. The implementation details of SR and RF models are described in *Appendix B, Section B.3.4*.

2.1 Software and Data Availability.

The model was developed in NetLogo. The source code to reproduce the outputs of this paper is available at CoMSES platform: https://doi.org/10.25937/8bf3-h968. Related experimental dataset is available at https://doi.org/10.17632/9v4byyvgxh.1. The complete description of this BNE-informed ABM following ODD+D protocol [32] is provided in *Appendix B*.

2.2 Improved BNE Behavioral Model.

2.2.1 Theoretical Background.

This research adopts Bayesian Nash Equilibrium (BNE) to simulate the decision-making process among rational and game-playing agents (evacuees). BNE is a widely adopted concept in game theory, which extends the standard framework of Nash equilibrium by accounting for the uncertainty brought by incomplete (private) information [33]. It describes a correlated equilibrium with diverse payoff gradients that adapt to different game conditions, encompassing the Nash Equilibrium as a specific instance, in contrast to the monotonic payoff gradient in the traditional Nash Equilibrium. Therefore, BNE is considered to be more realistic in an evacuation context when complete real-time information is generally missing for the individuals. In some real-world scenarios, participants may have no access to complete information for the strategies and payoffs of other players in the same game. They need to make their decisions only relying on their beliefs about others' strategies based on their experience and knowledge of the game [28]. BNE provides a more comprehensive framework to analyze the interactions of strategies taken by different participants in such scenarios, and an approach to updating the probabilities of others' decisions based on instant information obtained. It assumes that intelligent agents in this model make their decisions based on incomplete information, coinciding with individual information gaps occurring in reality [28]. That is, agents here participate in games with incomplete information, also called Bayesian games, and strive to maximize their expected utility to achieve a Bayesian Nash Equilibrium (BNE), defined as a Nash Equilibrium in a Bayesian game, where the strategies taken should be the optimal decisions to each other [29, 33].

Therefore, the primary element of individual decision-making is the probability distributions of the next strategies played by nearby participants, especially the possibilities of other players choosing the same strategy as the player in the same game. In this model, the rules of BNE are reflected as the probability distribution of nearby evacuees' next actions as well as a series of utility-related functions, quantifying interactive decision-making process of individuals in scenarios in varying spatial environments. BNE agents determine their next moves according to the *Total Utility* (U_{total}) of each navigable patch in their Moore neighborhood[3].

2.2.2 Utility Functions.

Each agent's final utility payoff is associated with the possible strategies taken by other agents, probable changes of their perceived surroundings and the physical distance from current location to the exit point. This research defines all BNE related utilities as patch attributes to reduce computational complexity of simulation process. It assumes that each BNE agent will consider the potential congestion levels of all passable patches in its Moore neighborhood and then choose one that could maximize its final utility payoff to move. A set of BNE utility functions have been proposed to quantify each patch's attraction (U_{total}) for evacuees.

This model defines that individual decision-makings depend on the total utility (U_{total}) of surrounding patches, which is relevant to three main parameters: *Distance Utility* (U_d), *Comfort Utility* (U_c) and *Expected Comfort Utility* (U_{ec}), and represented as the sum of U_d and U_{ec}, as shown in Eq. 1. That is, BNE evacuees take their next actions after accounting for the distance from their current positions to the exit, the number of evacuees who may move to the same patch as themselves in the next time step, and the possible moves of evacuees on their Moore neighborhood [28]. The adoption of BNE theory enables agents to avoid barriers and clogged areas appearing on their pathways by predicting the possible actions taken by other nearby agents, so as to select an alternative evacuation route with higher comfort level and shorter exit time. Each BNE agent will evaluate the total utilities of all the passable patches in their Moore neighborhood (see Fig. B.2) to decide where to move in the next time step. Relevant utility functions are shown as follows.

$$U_{total} = U_d + U_{ec} \tag{1}$$

A. Distance Utility

The term U_d is related to the distance from current position to the exit point and defined as an increasing attribute value with getting closer to the exit, as shown in Eq. 2.

$$U_d = \frac{D - d}{D} \tag{2}$$

Where, d represents the distance from the current patch to the exit; D refers to the diagonal distance of the simulation space containing Horizontal/Random Squares, and for Vertical Corridors mode, the value is set to be the route with the longest distance from one corner to the exit passing through two cramped bottlenecks.

B. Comfort Utility

The term U_c is defined as a series of coefficients essential to Expected Comfort Utility (U_{ec}), reflecting the individual comfort level in every navigable patch. According to the speed-density relation associated with the Spatial-Grid Evacuation Model (SGEM) [34] (see Eq. 5), the value was assigned as one when no more than two agents occupied this patch. The value of U_c was defined as a proportion of the free-moving speed (i.e. 1.4 m/s) related to the number of evacuees on the patch. That is, there is an inverse proportion of comfort utility

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[3] Moore Neighborhood refers to a square-shaped neighborhood with radius of one cell.

to the number of agents on the patch. Considering the limited space capacity in the real-world scenario, U_c was set to zero when over four agents occupied the same patch, as shown in Eq. 3.

$$U_c = \begin{cases} 1.00, & n \leq 2 \\ 0.51, & n = 3 \\ 0.07, & n = 4 \\ 0.00, & n \geq 5 \end{cases} \tag{3}$$

Where, n represents the number of evacuees on the patch.

C. Expected Comfort Utility

One of the main factors determining where an evacuee moves towards is the possible movements of his/her neighbors at next time step. In this model, Expected Comfort Utility (U_{ec}) is set as a dynamic patch attribute and defined as the multiplication of Comfort Utility (U_c) and the probability $p(n)$ that a certain number (n) of evacuees will move to this patch at the next time step. This calculation accounts for the possible responses of both the evacuee and the other agents on its Moore neighborhood, as illustrated in Eq. 4.

$$\begin{aligned} U_{ec} &= \sum\nolimits_{0}^{\mathrm{n}} p(n) U_c(n) \\ &= \sum\nolimits_{n=0}^{4} C_N^n {P_m}^n (1 - P_m)^{N-n} U_c(n) \end{aligned} \tag{4}$$

Where, n represents the number of agents on this patch; $U_c(n)$ refers to the individual comfort utility that a specific number (n) of agents occupying this patch at the next time step; N refers to the total number of evacuees on this patch and its Moore neighbourhood; P_m represents the probability of agents moving to this patch, defaulting to a random value in a range between 40% and 60%. The median, with a default setting of 50%, can be regulated through the slider *Probability-competing*.

D. Speed Calibration

This model assumes that individual moving speed should be dynamic instead of a static attribute. In real-world scenarios, the variation of moving speed is closely associated with the crowd density in the surroundings and the speed attribute in this model should be calibrated accordingly. On this basis, several of the main pedestrian speed-crowd density models that were widely adopted in recent years [35-37] have been compared and the Spatial-Grid Evacuation Model (SGEM) [34] was considered as an appropriate speed-density relation model for this research, as it accounts for both social interactions and the potential influences of local communications among pedestrians on individual moving speed [28].

In this model, the moving speed of each agent is tailored based on crowd density in surrounding area (i.e. the patch occupied and patches in its Moore neighborhood) and keeps updating every time step throughout each simulation run. The speed-density relation in this study is in accordance with the Spatial-Grid Evacuation Model (SGEM) [34], and individual speed regulations depend on the reference speed assigned through the slider *Moving-speed* at model initialization with a default value of one patch per time step. The individual moving speed is inversely proportional to the number of neighboring evacuees. Specifically, the general trend among these speed-density relation models remains consistent when the crowd density is lower than 4 person/m^2 , with pedestrians in a free-moving status at the speed of around 1.4 m/s. Pedestrians are considered to be in a state of constrained motion and move at approximately 0.1 m/s when the crowd density is greater than 8 person/m^2 . And when the crowd density ranges between 4 and 8 person/m^2, pedestrian movements start being restricted and their moving speed reduces with the increasing number of persons [28]. Since the average step length of adults is around 0.7 meter with an average response time of about 0.5 second [38], several related parameters were adjusted in the SGEM model to match the settings of simulation space. In this model, the reference speed can be adjusted through the slider *Moving-speed* rather than imposing a fixed value (e.g. 1.4 m/s), and individual moving speed is set to be in an inverse proportion to the number of evacuees (i.e. crowd density) on its Moore neighborhood. As high crowd density has a decay influence on individual moving speed, evacuees encircled by a crowd of agents are incapable of hopping large distances to a free patch near the exit. On this basis, the suitable speed-density relationship for this model is demonstrated in Eq. 5.

$$V = \begin{cases} 1.4, & 0 < \rho \leq 4 \\ 0.03\rho^2 - 0.64\rho + 3.36, & 4 < \rho < 8 \\ 0.1, & \rho \geq 8 \end{cases} \tag{5}$$

where, ρ is density of agents on the patch and its Moore neighborhood.

The relationship and derivation process of relevant BNE utilities is briefly illustrated in Fig. 3. The full details of the crucial components forming total utility (U_{total}) can be found in *Appendix B, Section 3.4.3*.

Total Utility **Distance Utility** **Expected Comfort Utility**

$$U_{total} = U_d = (D-d)/D + U_{ec} = \sum_0^n C_N^n {P_m}^n (1-P_m)^{N-n} U_c(n)$$

$$V = \begin{cases} 1.4, 0 < \rho \leq 4 \\ 0.03\rho^2 - 0.64\rho + 3.36, 4 < \rho < 8 \\ 0.1(\approx 0), \rho \geq 8 \end{cases} \qquad U_c(n) = \begin{cases} 1.00, n \leq 2 \\ 0.51, n = 3 \\ 0.07, n = 4 \\ 0, n \geq 5 \end{cases}$$

Speed-Density Relationship (SGEM) **Comfort Utility**

Figure 3 The schematic diagram of *Total Utility* (U_{total}) and related utilities. The equation of *Comfort Utility* (U_c) is derived from the SGEM speed-density relationship. Where, ρ represents the density of agents on the patch and its Moore neighborhood.

2.2.3 Improved Details.

The initial version of the BNE behavioral model [39] implemented agent movement by a utility maximization approach in which 100% of agents choose the patch with the highest total utility to move. However, the experimental results revealed that this decision-making criterion might induce all agents on the same patch to take coincident actions especially in the latter stages of simulations, leading to local congestion and low evacuation speed [28]. In this case, the patch with the highest total utility definitely cannot be their best choice to move at next time step. This is an important issue caused by the excessive pursuit of simplifying computational complexity and neglecting the heterogeneity in agents. Some errors occurred in the conversion process from individual utility payoffs to patch attractions as well as the BNE related calculations. This research addressed above challenges by including some noise to the individual probability of taking each strategy (P_m). The term $P_m$has been changed from a fixed value of 50% to a random value selected within a predefined range from 40% to 60%. In this model, each evacuee has been assigned a specific value of P_m to mitigate potential biases introduced by a fixed parameter setting, thereby contributing to the overall robustness of this model. The range of P_m can be configured via the corresponding slider in the model to improve the model's adaptability to diverse scenarios.

Furthermore, this research has also introduced variability into the initial decision-making criterion of BNE agents and proposed a multi-strategy combination: with around 80% of agents selecting the patch with the highest U_{total}, 15% choosing the patch with second-highest U_{total}, and 5% selecting the patch with third-highest U_{total}, to assist intelligent BNE agents in dispersing and taking the best responses to each other. In this model, all BNE related utilities are computed at the beginning of each simulation and updated every time step. The patches representing impassable blockages have been excluded from BNE-related calculations. The patch visited by a BNE agent in the last time step will be removed from the candidate patch-set that this agent intends to move at the next time step to avoid being trapped where it was.

2.3 Experimental Design.

The hypothetical evacuation space (Fig.4) was made up of 1360 (68*20) patches where multiple occupations for each of them are allowed in this model, making it possible to explore whether and how this model can simulate emergent patterns of pedestrian behaviors in evacuation scenarios with different environmental contexts.

Three sets of experiments – each containing 12750 simulations i.e. 382500 runs in total - were conducted in NetLogo BehaviorSpace under different environmental and behavioral contexts, by varying several model parameters:

1) *Barriers-mode*. Three types of barriers were explored, which are Horizontal Corridors, Vertical Corridors, and Random Squares, standing for corridors (alleys), bottlenecks and intersections as noted above. These were designed to assess model performance in simulating unexpected patterns of human evacuating behaviors in varied constricted spaces. The layouts of simulation space are shown in Fig. 4.

2) *Moving-pattern*. As previously stated, three types of behavioral models were explored, which are Shortest Route (SR) model, Random Follow (RF) model, and BNE model. These were developed to reproduce various pedestrian behaviors (e.g. shortest pathfinding and leader behavior, etc.) in emergency situations. Each agent (i.e. evacuee) was assigned one of the above behavioral models and adhered to this decision-making logic throughout each simulation. The detailed description of simulation experimental design is provided in *Section B.3.2* in *Appendix B*.

The model also mixed intelligent BNE agents with relatively naïve ones (i.e. evacuees following the SR/RF model) in proportions from 0% to 100% at intervals of 2% in order to further explore the impact of intelligent and game-playing agents in the crowd. Two agent combinations (i.e. BNE-SR and BNE-RF) have been investigated in this research. Table 1 provides a brief overview of the key parameters in each set of experiments. The full details of experimental parameter settings are outlined in Table B.4.

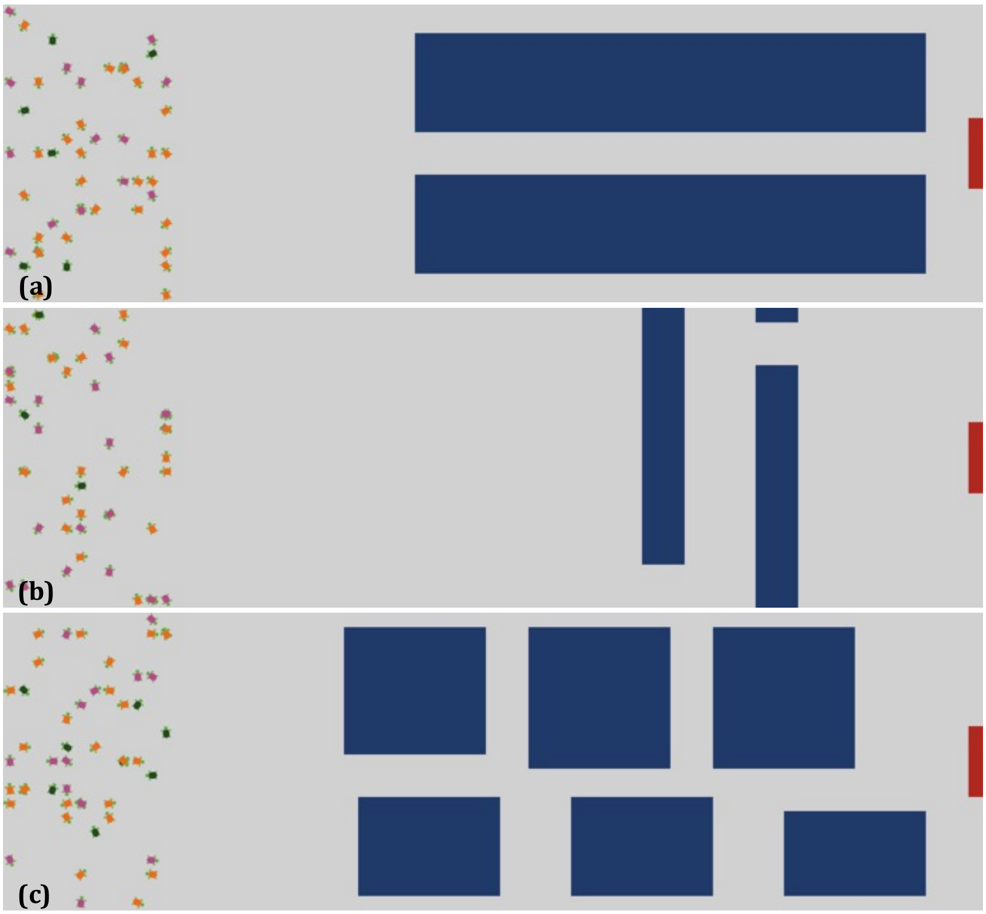

Figure 4 The interfaces of the simulation space with different barrier modes: (a) Horizontal Corridors (narrow alleys), (b) Vertical Corridors (bottlenecks), and (c) Random Squares (intersections). The exit is represented by the red patches and the blue ones represent the barriers in the simulation space. The corridor width and sizes of blockages in all modes can be adjusted through the corresponding sliders in the ABM.

Table 1 The list of key parameter settings in the experiments.

Parameters	**Values (Exp.1)**	**Values (Exp.2)**	**Values (Exp.3)**	**State**
Number-of-Evacuees	2000	2000	2000	Static
Moving-pattern	BNE mixed with SR/RF	BNE mixed with SR/RF	BNE mixed with SR/RF	Dynamic
Barriers-mode	Horizontal Corridors	Vertical Corridors	Random Squares	Static
Corridor-width	1, 2, 3, 4, 5.	1, 3, 5, 7, 9.	N/A	Dynamic
Barriers-side-length	N/A	N/A	11, 10, 9, 8, 7.	Dynamic
Percent-of-BNE-evacuees	0%~100% (+2%)	0%~100% (+2%)	0%~100% (+2%)	Dynamic
Repetitions	50 simulations were conducted at each BNE percentage fraction *(12750 simulations in this set of experiment)*	50 simulations were conducted at each BNE percentage fraction *(12750 simulations in this set of experiment)*	50 simulations were conducted at each BNE percentage fraction *(12750 simulations in this set of experiment)*	N/A

Values collected	Exit time; Average expected comfort utility	Exit time; Average expected comfort utility	Exit time; Average expected comfort utility	N/A

3 Results

3.1 Horizontal Corridors.

The model was first evaluated in an evacuation space involving three horizontal corridors with adjustable widths, to explore the relationship between evacuation efficiency and individual intelligence in complicated spaces with varied levels of constriction. The agents with high intelligence (i.e. BNE evacuees) were mixed with the naïve agents (i.e. SR/RF evacuees) at varying proportions to simulate evacuations under different levels of individual intelligence. Fig. 5 shows the variation in evacuation time with an increasing proportion of intelligent BNE agents for varied constricted spatial environments. A local line of fit is shown in each plot with 95% confidence interval. Fig. 5 indicates that an increasing ratio of intelligent agents provides little advantage for evacuation efficiency in highly constricted spaces (i.e. scenarios with the width of the middle corridor setting to 1 and 2 patches respectively). This is because highly confined spaces result in limited or no alternative strategies for agents to take, and thus the extra intelligence of BNE has minimal effects on reducing exit time. A clear reduction in evacuation time is found with increasing BNE proportion with wider corridors. The same correlation among individual intelligence, evacuation efficiency and spatial constricted level was found in both BNE combinations (BNE-SR and BNE-RF).

The screenshots in Fig. 6 illustrate what happens during evacuations. All of the naïve SR agents (shown in green) follow the shortest route (i.e. the middle corridor) to the exit point (i.e. red patches). The intelligent BNE agents (shown in orange) have the capability to disperse (Fig. 6A) or turn around (Fig. 6B) and choose a different route in anticipation of the crowded path ahead, despite it potentially being longer. The multiple path selections of intelligent agents in this model could be better represent individual evacuating behaviors in real-world scenarios, compared to the single evacuation route taken by naïve agents. The incorporation of Bayesian game theory brings the extra intelligence into agent navigation in high-density and life-threatening situations, as BNE agents adopt strategies to avoid barriers and crowds in advance, by considering the potential moves of other agents.

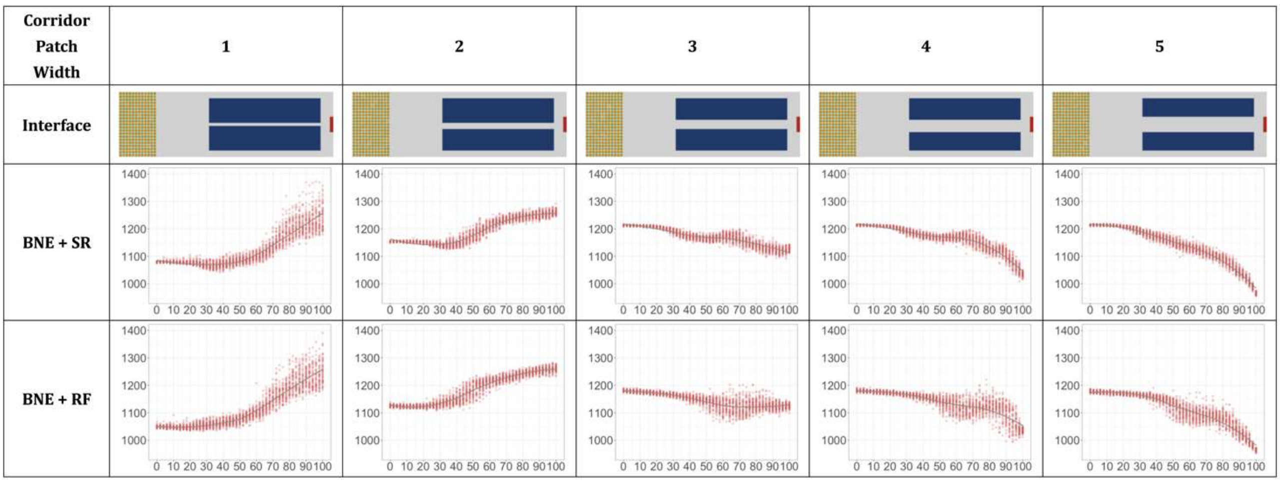

Figure 5 Plots of evacuation time (y-axis) against the percentage of BNE-SR and BNE-RF combinations (x-axis) in complicated space with varied horizontal corridor widths from 1 to 5 patches at a 1-patch interval, for 2000 evacuees, with 50 simulations conducted for each BNE percentage fraction in Horizontal Corridors. (12750 runs in total)

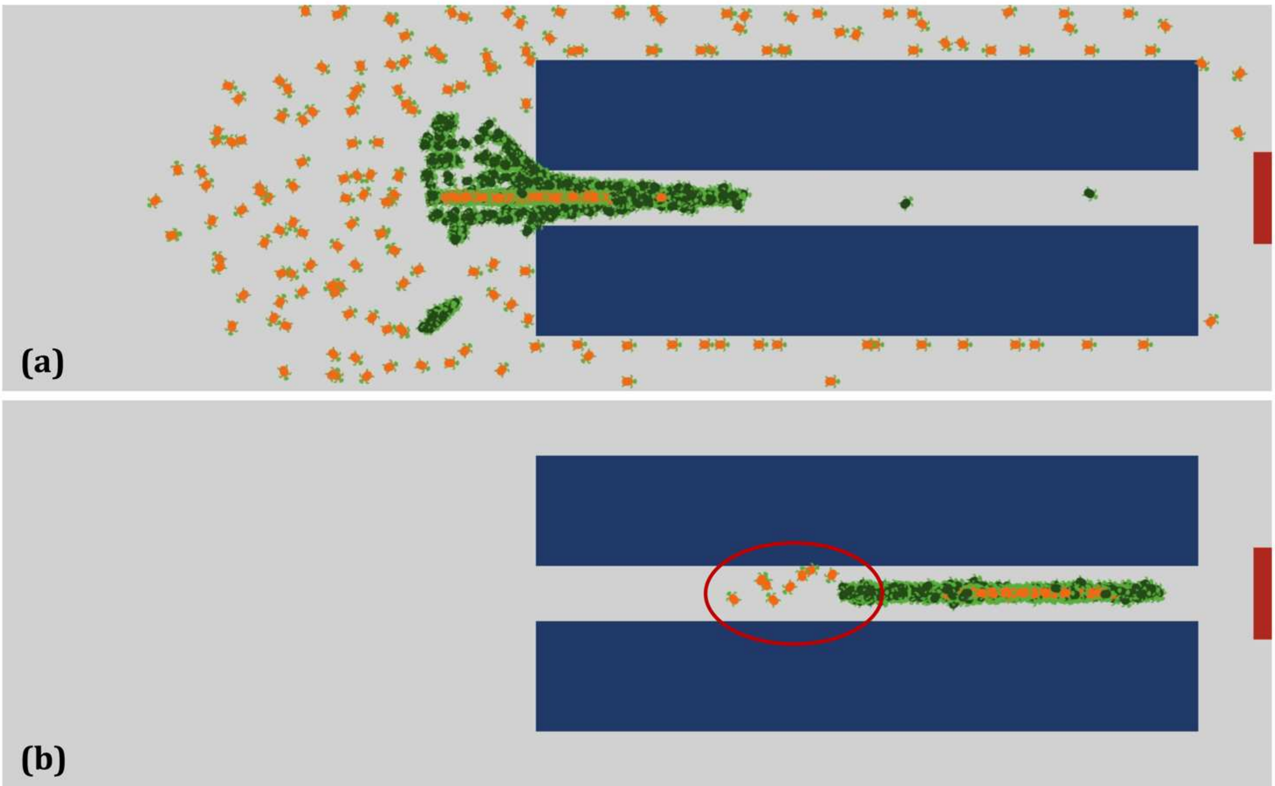

Figure 6 An illustration of evacuees in the BNE-SR combination, with intelligent agents (BNE) shown in orange and naïve agents (SR) shown in green in a Horizontal Corridor with a 3-patch width. Intelligent agents in the red circle display turning behaviors in anticipation of a crowded path ahead.

3.2 Vertical Corridors.

A second set of model assessments was undertaken using a heavily confined space with narrow bottlenecks in order to explore the emergent behaviors of BNE agents in varying constricted spatial environments. Fig. 7 shows how evacuation times change with increasing proportion of BNE agents, in a space with different levels of constriction. Similar to the results displayed in Fig. 5, the increasing BNE ratio may negatively affect evacuation efficiency in highly confined spaces (i.e. scenarios with the bottleneck set to 1 or 3 patches). However, little advantage was brought by BNE in reducing evacuation time even with wider bottlenecks. One of the main causes is that only one exit route option - evacuating through two bottlenecks - is available in these scenarios and extra BNE intelligence has done little to shorten evacuation time in these cases. Thus, this research identifies a situation where there is a case for little or no alternative intelligent strategy (i.e. evacuation route) in scenarios with highly cramped bottlenecks. In such cases, where space and thus route choices are extremely limited, additional intelligence and game-playing of BNE agents negatively affects evacuation efficiency – they effectively outsmart themselves.

To unpick this finding, the evacuation process was examined in more detail in spaces containing varying cramped bottlenecks. Fig. 8A shows how none-BNE agents (shown in green) follow the shortest exit route and form a long queue during evacuations. Some of the BNE agents (shown in orange) were trapped in the corner and cannot navigate to the relatively uncrowded area. This illustrates how that in highly constricted spatial environments, more BNE agents attempt to employ strategies instead of exiting directly and how this is detrimental to their evacuation efficiency. In some instances, clogging was found at bottlenecks where a large group of agents competed to evacuate through the narrow space (Fig. 8B). In such circumstances, with a highly confined space offering few route options, a large proportion of intelligent BNE agents may have a negative impact on evacuation efficiency.

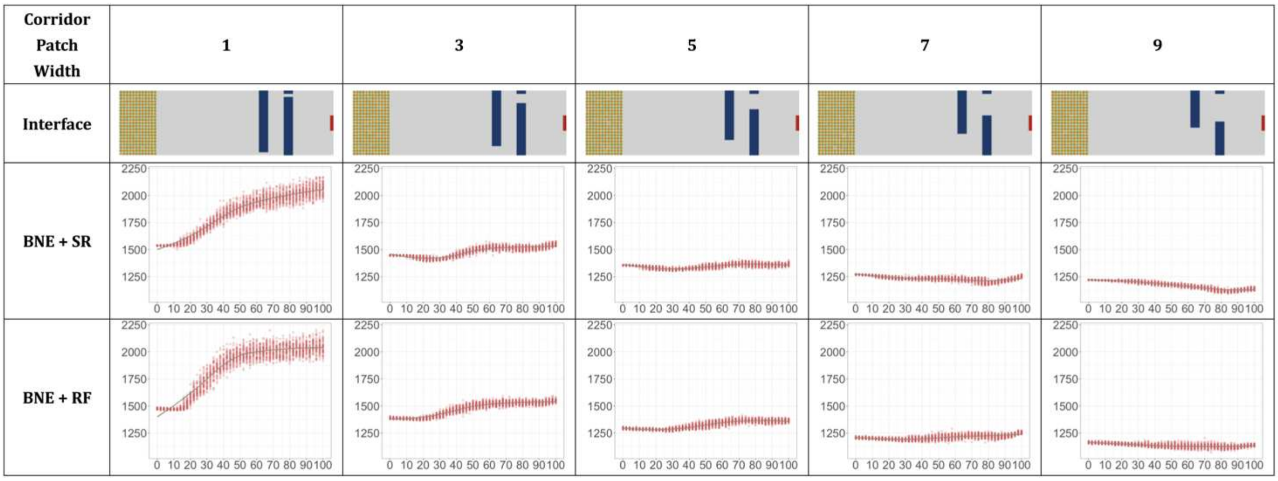

Figure 7 Plots of evacuation time (y-axis) against the percentage of BNE-SR and BNE-RF combinations (x-axis) in a complicated space with varied vertical corridor widths from 1 to 9 patches at a 2-patch interval, for 2000 evacuees, with 50 simulations conducted for each BNE percentage fraction for Vertical Corridors. (12750 runs in total)

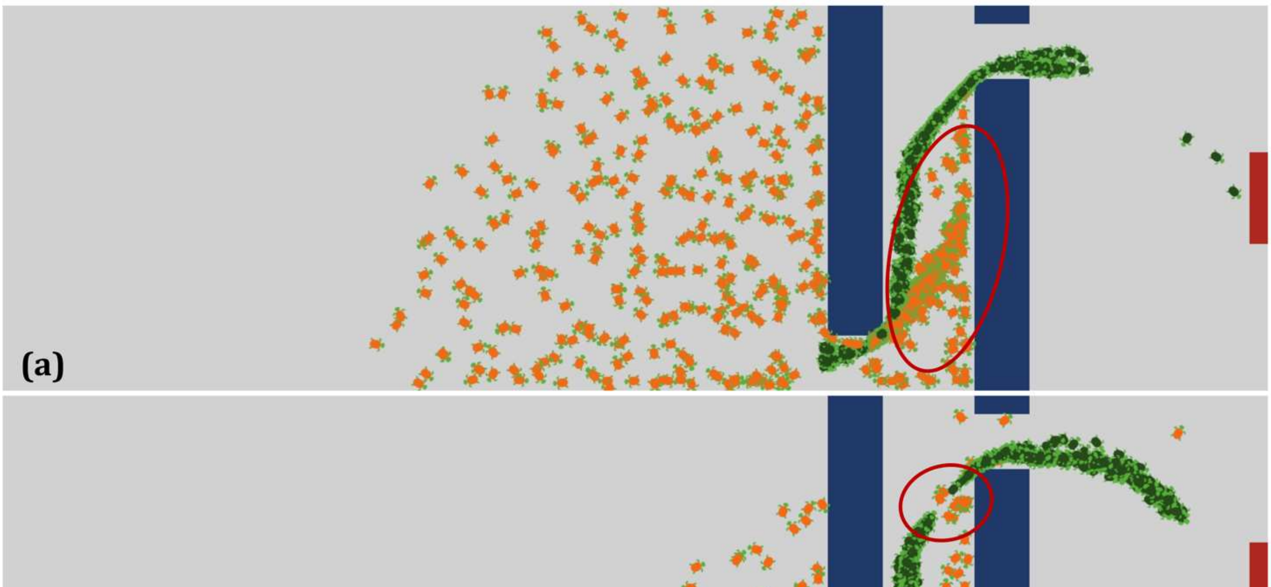

Figure 8 An illustration of evacuees in the BNE-SR combination, with intelligent agents (BNE) shown in orange and naïve agents (SR) shown in green for a Vertical Corridor with a width of 3 patches. Intelligent agents in the red circle (a) were blocked in the corner and would navigate to the relatively uncrowded area when they have more route options, as marked in Fig.8(b).

3.3 Random Squares.

It is difficult to capture salient herding behavior in a highly crowded space with few choices of strategies available to be played, as people generally consider that the optimal survival strategy is to avoid the majority and find an alternative evacuation route [40]. The above results (see Fig. 6 & 8) illustrate that intelligent BNE agents may choose an alternative path rather than following the shortest exit route in highly constricted spatial environments. However, it is hard to distinguish herding with more intelligent behaviors in such cases, because the spaces are so confined that intelligent agents have little room to navigate the space better than others. Consequently, this research relaxed the level of spatial constriction in a simulation environment containing multiple square barriers, in order to provide intelligent agents with more route choices and to better observe collective behaviors during evacuations. Fig.9 shows a consistent reduction in evacuation time in all scenarios with the increasing proportion of BNE evacuees, suggesting that agents with BNE were able to employ their intelligence when they have more routes to choose from in extremely constricted spaces. A gradually significant benefit from BNE intelligence in improving evacuation efficiency was also found with relaxing levels of spatial constriction.

Fig. 10 illustrates evacuations in which herding behaviors were captured in both agents with high and low intelligence during evacuations. Naïve (none-BNE) agents (shown in green and magenta) follow the decisions taken by the majority, resulting in collective behaviors being observed across various evacuation contexts. For intelligent (BNE) agents (shown in orange), noticeable herding behaviors were also captured in the situations when they need shift their original escape direction to one of the nearby corridors (see Fig. 10A). It was also found that intelligent agents displayed evident herding behavior in cramped bottlenecks when their proportion was over 50%. Fig. 10B & 10C indicate that intelligent evacuees also tend to cluster similar to naïve agents in the latter half of simulations due to the lack of route choices. This finding has important implications in urban space design suggesting that evacuation routes need to be devised to take advantage of the intelligence and BNE behaviors.

Large crowd gatherings can lead to very dense public space, resulting in discomfort, injuries, and even deaths during serious trampling incidents. In this research, an Expected Comfort Utility parameter, U_{ec}, was used to represent individual agent comfort levels and recorded at every time step over each simulation run. An average value of agent comfort levels was then calculated at the end of each run. As shown in Fig. A.1-A.3, this average U_{ec} shows a significant uptrend with increasing ratio of BNE agents in all scenarios, indicating that although intelligent BNE agents perform better with more personal space, herding behaviors are still observed in both naïve and intelligent agents (Fig. 10). The variations in average U_{ec} also indicate that the intelligence from BNE can still make a difference in high-density and life-threatening situations by improving individual comfort levels and reducing the chances of injuries or deaths among evacuees, even if it does not necessarily improve evacuation efficiency in these cases.

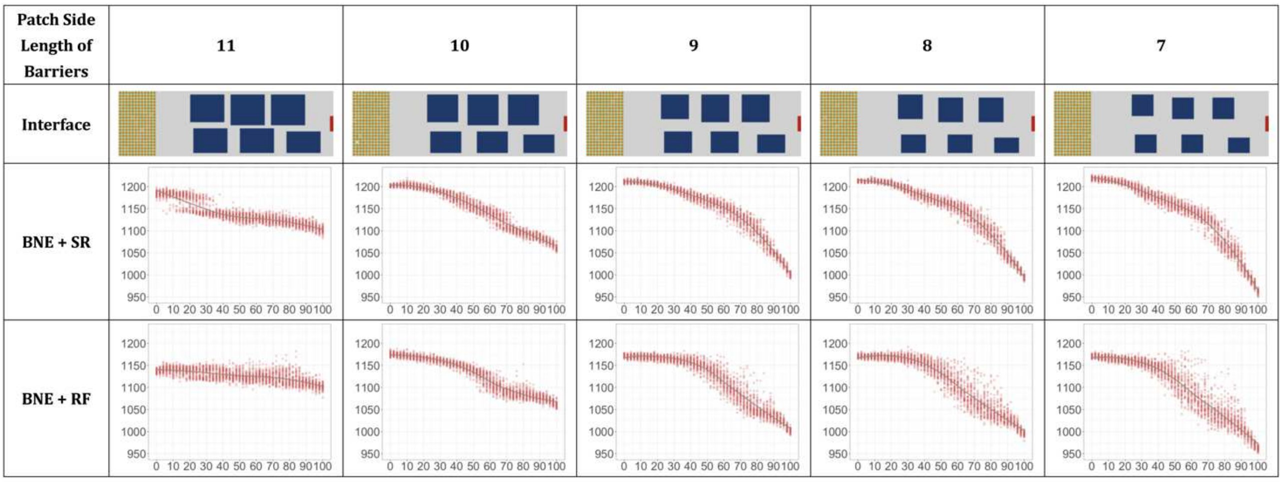

Figure 9 Plots of evacuation time (y-axis) against the percentage of BNE-SR and BNE-RF combinations (x-axis) in complicated space with varied barrier side-lengths from 11 to 7 patches at a 2-patch interval, for 2000 evacuees, with 50 simulations conducted for each BNE percentage fraction in Random Squares. (12750 runs in total)

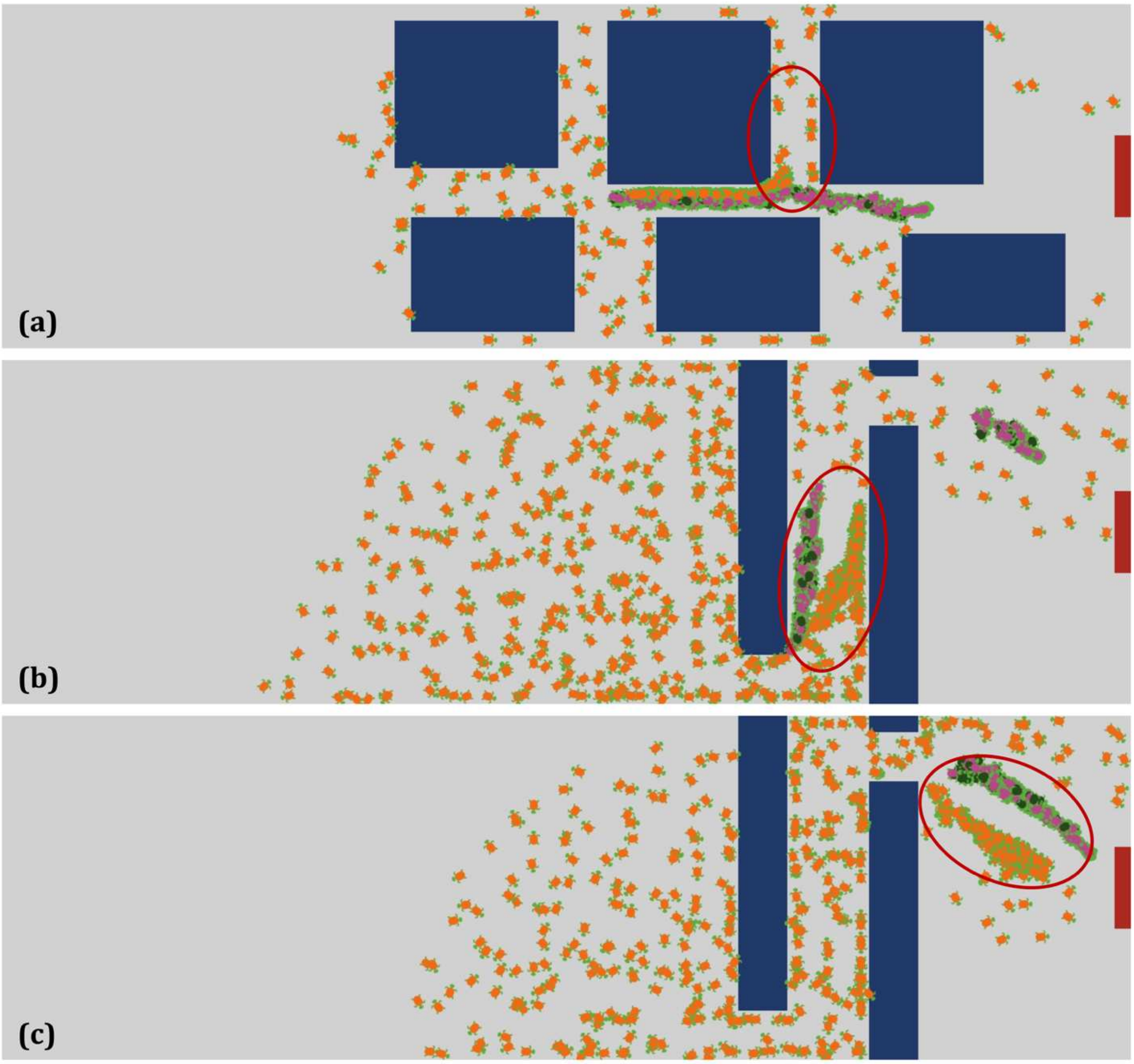

Figure 10 An illustration of evacuees in the BNE-RF combination, with intelligent agents (BNE) shown in orange and naïve agents (SR agents shown in green; RF agents shown in magenta), with Narrow Corridors and Random Squares. Both intelligent and naïve agents highlighted in red circles display salient herding behaviors during evacuations.

4 Discussion

The performance of the BNE-informed model, as shown through the evacuation times and illustrations, suggests how simulation models incorporating such agent intelligence can reproduce individual behaviors in real-world scenarios. This model implements an evacuee response to their perceived surroundings in an integrated approach that considers both physical constraints and real-time information (e.g. potential actions of other nearby agents). This in turn makes it possible to model emergent patterns of evacuation behaviors in varying constricted spatial environments. This research overcomes individual information gaps through Bayesian Nash Equilibrium (BNE) in which players could adapt their next strategies by predicting the actions of others, closely matching the real-world context of incomplete real-time information when evacuating from a complicated space. In this way, this BNE-informed ABM is able to accurately simulate individual behaviors in life-threatening situations where spaces contain blockages and congestion-inducing barriers and objects. It provides an agile way to explore crowd management, evacuation planning, as well as the design of public spaces (e.g. train stations, theatres, schools, and universities, etc.) [3]. It considers intelligent and game-playing behaviors of individual agents in order to understand the impact of their behaviors on evacuation efficiency, comfort level and the probability of accidents. Additionally, the results also indicated that more than one solution should exist for an evacuation scenario so as to assist BNE agents in finding other solutions besides shortest path or randomly following another agent. The findings suggest that evacuation plans with multiple viable alternatives could accommodate varying human emergent behaviors and better reduce the risk of stampedes to protect public safety.

This examination of BNE-informed ABMs explored the characteristics of intelligent agent behaviors. The model is capable of simulating various established crowd behaviors (e.g. herding behavior, self-organized queuing behavior, leader behavior, etc.) depending on various spatial contexts. Intelligent agents in this model perform a series of BNE-related calculations based on anticipated future movements of other agents nearby. It is one of the first crowd-simulation models to incorporate intelligent and game-theoretical pedestrians especially in highly crowded spaces [40]. The results demonstrate that BNE-intelligent agents can exhibit established pedestrian patterns (e.g. herding and self-organized queuing, etc.) in different evacuation scenarios. The evacuation illustrations indicate that agents tend to follow neighbors with shared preferences, i.e. similar decision logic, demonstrating strong social interactions among rational agents [41]. It was also shown that this model captures the adverse impacts of outsmarting behaviors on individual decisions in situations with limited strategies, in which people may get little benefit from having higher intelligence, sometimes this outsmarting can even negatively affect their efficiency.

The study has demonstrated several basic principles of group forming and crowd avoidance that resonate with the literature. However, there are several limitations in the current research: 1) Finding an appropriate reference dataset for model validation is very challenging at the current stage. The authors have attempted to introduce some realistic and spatially articulated datasets to validate the emergent behaviors of agents, yet most are inapplicable to the current study. Specifically, evacuation video databases [42, 43] generally focus on people's first responses (e.g. filming, delayed actions, etc.) to emergency incidents [44]. It is a difficulty to capture the nuances between individual emergent behaviors during evacuations in dense public spaces through some video clips with limited sample size. Related questionnaire survey data [45, 46] describes people's likely behaviors under emergencies. The issue is that it is hard to understand and predict the actual responses of the participants in real emergency situations in hypothetical studies. Although we acknowledge the challenges in obtaining suitable datasets for model validation, future research could focus on incorporating advanced data collection methods to bridge this gap. One promising approach is the utilization of virtual reality (VR) environments combined with human participants. VR simulations could replicate emergency scenarios with controlled variables in order to capture detailed data on individual/group behaviors during extreme panic. Such data could provide quantifiable metrics for validating the model's predictions, such as evacuation time, decision-making processes, crowd movement patterns, etc. Modeling pedestrian dynamics in public buildings involving varying facilities and elevations is more complex than those in an abstracted 2D space, which is also a matter of concern in the ongoing research. 2) The current model could be further improved to simulate the emergent behaviors displayed by agents who get stuck in the crowd. This research assumes that intelligent agents are repelled by large congestions and mainly focuses on modelling evacuating behaviors that avoid barriers and clogged areas. Here the simulations were conducted in highly constricted spatial environments, with little opportunity to clearly observe the interactions between agents blocked in the congestion. Therefore, a simulation space with appropriate environmental context and additional cognitive approaches based on behavioral heuristics [24] could be further incorporated within this ABM to provide a more comprehensive simulation of pedestrian dynamics, and to reproduce emergent patterns of individual evacuating behaviors in crowded spaces.

5 Conclusions

In conclusion, crowd dynamics in complicated real-world environments (e.g. shopping centers and train stations, etc.) can be highly complex due to a variety of factors including heterogeneous individual behaviors, diverse spatial structures and public facilities that influence pedestrian motion. This model provides a platform to unpick intelligent behaviors and underlying interactions among pedestrians in emergency situations, explaining why crowd behaviors in life-threatening and high-density situations appear similar regardless of intelligence. Intelligent game-playing agents can exhibit various unexpected behaviors in emergency situations, matching crowd evacuations in real-world scenarios. They can evacuate effectively in uncrowded spaces with low blockages but are puzzled in densely populated areas with high constriction level, limiting their strategies and route choices. The model can be further applied to understand individual reactions and crowd behaviors during life-threatening circumstances such as serious stampedes (e.g. Seoul Halloween crowd crush in Fig. 1) and potential safety hazards in public spaces (e.g. large congestions at narrow entrances of metro stations in Fig. 2). The model also explains why intelligent BNE agents seemingly display herding behavior in confined spaces with fewer route choices. These findings have critical implications for urban space design suggesting that evacuation routes, entry points and emergency facilities need to be designed to take advantage of human intelligence. This BNE-informed model offers opportunities to simulate human behaviors and individual responses during extreme social or natural events [2, 27, 47], such as in crowded social gatherings, social unrest, and evacuations during a natural disaster, etc., to support the formulations of urban emergency preplanning as well as policies for effective crowd management.

Appendices

Appendix A. Facets: Variations in Expected Comfort Utility

Fig. A.1-A.3 illustrate how the average expected comfort utilities change with the increasing proportion of BNE agents in varying constricted spaces. Related barrier settings were tailored to create simulation space with varied levels of spatial constriction.

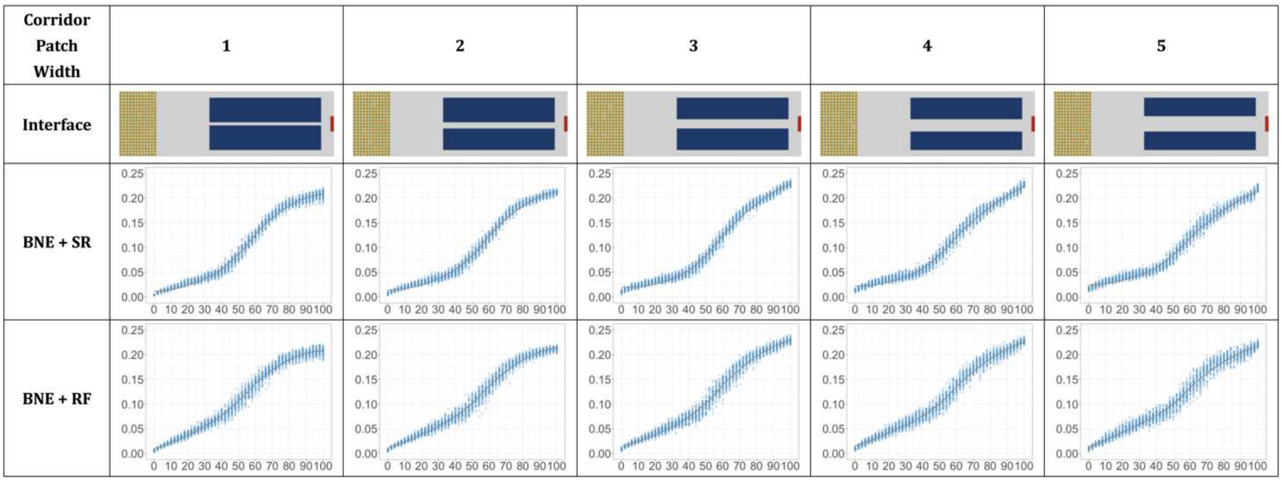

Figure A.1 Plots of average expected comfort utility (y-axis) against the percentage of BNE-SR and BNE-RF combinations (x-axis) in a complicated space with varied horizontal corridor widths from 1 to 5 patches at a 1-patch interval, for 2000 evacuees, with 50 simulations conducted for each percentage fraction in Horizontal Corridors (12750 runs in total).

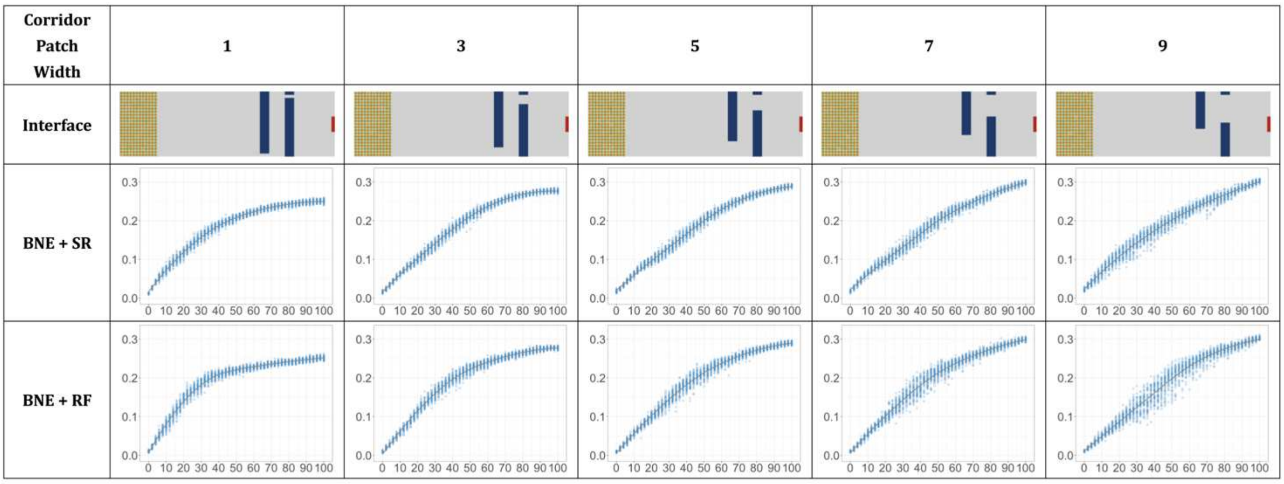

Figure A.2 Plots of average expected comfort utility (y-axis) against the percentage of BNE-SR and BNE-RF combinations (x-axis) in a complicated space with varied vertical corridor widths from 1 to 9 patches at a 2-patch interval, for 2000 evacuees, with 50 simulations conducted for each percentage fraction in Vertical Corridors (12750 runs in total).

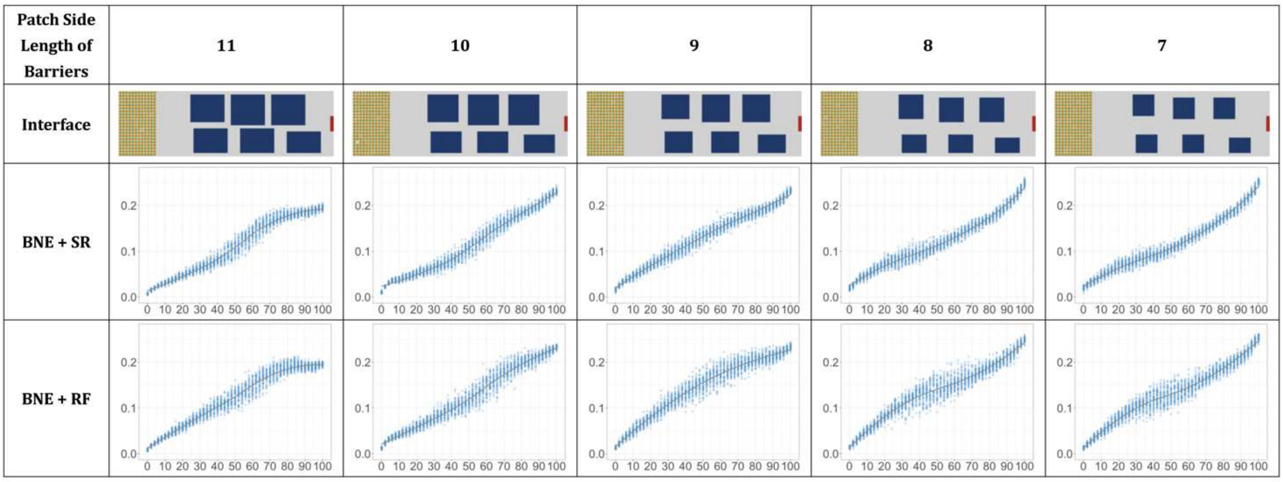

Figure A.3 Plots of average expected comfort utility (y-axis) against the percentage of BNE-SR and BNE-RF combinations (x-axis) in a complicated space with varied barrier side lengths from 11 to 7 patches at a 2-patch interval, for 2000 evacuees, with 50 simulations conducted for each percentage fraction in Random Squares (12750 runs in total).

Appendix B. Model Description (ODD+D protocol)

Our research proposes an agent-based model (ABM) incorporating Bayesian game theory into pedestrian simulation to simulate the emergent patterns of individual behaviors with strong applicability. Bayesian Nash Equilibrium (BNE) was adopted to simulate the interactive decision-making process among rational and game-playing agents. A complete description of this BNE-informed ABM following ODD+D protocol [32] is provided.

1 Overview

1.1 Purpose

This ABM ultimately aims to provide a realistic description of complicated pedestrian behaviors especially in high-density or life-threatening situations. To achieve it, Bayesian Nash Equilibrium (BNE) was introduced to bring extra intelligence into agent navigations and to simulate social interactions among individuals. The implementations of three behavioral models, which are *Shortest Route (SR) model*, *Random Follow (RF) model*, and *BNE model*, make it possible to reproduce emergent behaviors of pedestrians (e.g. shortest pathfinding and leader behaviors, etc.) in emergency situations.

1.2 Entities, state variables and scales

The model contains three main types of entities: **Patches** (i.e. simulation space), **Evacuees** (i.e. agents) and **Nodes** applied to reproducing shortest pathfinding. The names of state variables here are same as those implemented in NetLogo.

The **Global Environment** is defined as model parameters at the system level, which involves all the global variables relating to simulation environmental settings. See Table B.1 for an outline of global environment state variables.

Table B.1 Global Environment state variables

Variable Name	Variable Type and Units	Brief Description
Number-of-Evacuees	numeric	Total number of evacuees participating in simulations.
Percentage-of-BNE_evacuees	%	The proportion of evacuees following BNE behavioural model.
Probability-competing	%	The probability that an agent moves to this patch at next time step.
Exit-width	patches	The width of the exit.
Moving-speed	patch per tick	The reference speed (i.e. free-moving speed).
Radius	patches	The vision distance of evacuees deferring to Random Follow (RF) model; Assigning evacuees a "cone of vision" with a viewing angle of 60 degrees in front of themselves.
Corridor-width	patches	The width of narrow corridors.
Percent-of-RFleaders	%	The proportion of leaders against the total number of evacuees using RF model.
Barriers-side-length	patches	The side length of square barriers; It is used in Random Squares barrier mode.
Initial-position	%	The proportion of the area that evacuees occupied in model initialisation against the initial simulation space.
Moving-pattern	chooser	4 patterns are available: Shortest Route (SR), Random Follow (RF), BNE mixed with SR, and BNE mixed with RF.
Barriers-mode	chooser	3 types of barriers are available: Horizontal Corridors, Vertical Corridors, and Random Squares.
weight-Ud	numeric	A coefficient to balance the influence of distance utility and expected comfort utility on the decision-making process of BNE evacuees.
weight-Uec	numeric	A coefficient to balance the influence of expected comfort utility and distance utility on the decision-making process of BNE evacuees.

Patches compose the simulation environment. In this model, evacuation space consists of 1360 (68*20) patches with a set of patch state variables. These utility-related attributes provide support for modelling interactive decision-making process of rational and game-playing agents. Details of patch state variables are shown in Table B.2.

Table B.2 Patch state variables

Variable Name	Variable Type and Units	Brief Description
Uec	numeric	Expected Comfort Utility
Ud	numeric; static	Distance Utility, related to the distance from current location to the exit.
U-total	numeric	Total Utility, refers to the sum of Distance Utility and Expected Comfort Utility.
barrier?	True/False	Whether or not the patch is set as a barrier.
exit?	True/False	Whether or not the patch is set as the exit.
N-total	numeric	The total number of evacuees who have a certain probability to move to the patch at next time step.

Evacuees represent the agents participating into evacuation simulations. Each evacuee (i.e. agent) has been assigned one of three behavioral models (i.e. SR, RF, and BNE models) and remained following the decision-making logic allocated over each simulation. The related state variables are shown in Table B.3.

Table B.3 Evacuee state variables

Variable Name	Variable Type and Units	Brief Description
target	patch	The patch that this evacuee currently tends to move to.
speed	m/s	The moving speed of each evacuee during simulations, which is inversely proportional to the increasing crowd density in the evacuee's Moore neighborhood.
leader?	True/False	Whether or not this evacuee is a leader, used in Random Follow moving pattern.
follow?	True/False	Whether or not this evacuee is following others, used in Random Follow moving pattern.
nearby-leaders	agentset	The leaders in views who can be selected to follow during evacuations, used in Random Follow moving pattern.
my-leader	agent	The leader that this evacuee is currently following.
last-patch	patch	The patch that this evacuee stayed at the last time step.
BNE?	True/False	Whether or not this evacuee follows BNE behavioural model.
U_ec	numeric	The expected comfort utility of each evacuee.
exits	nodes	The nodes located on the exit patches, only used in Shortest Route moving pattern.

Nodes refer to the markers placed over the simulation space to support for reproducing shortest wayfinding strategy of SR evacuees.

Scales. The spatial extent of this model is an enclosure rectangular area of 68 * 20 square patches (see Fig. B.1), in which evacuees can only evacuate through the exit on the right side. The model keeps running until all the evacuees leave the simulation space. That is, no absolute temporal scale exist in this model and the value of time step depends on the initial environmental and individual settings.

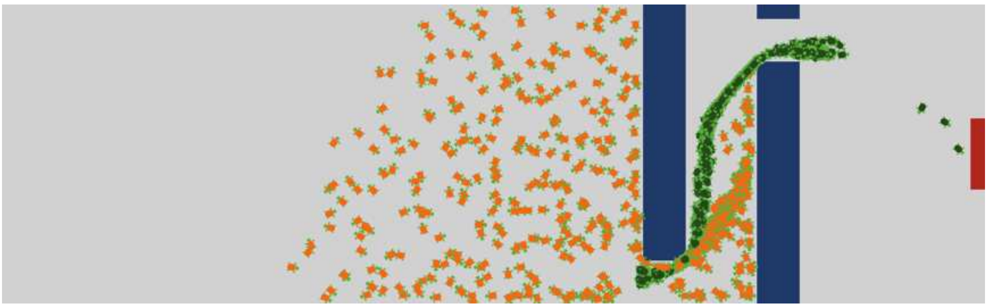

Figure B.1 The interface of the simulation model, with barriers in blue and exit in red for Vertical Corridors.

1.3 Progress Overview and Scheduling

This ABM simulates complete pedestrian evacuation processes in varied constricted spatial environments and reproduces interactive decision-making process of agents (i.e. evacuees) following different behavioural model (i.e. SR, RF, and BNE models). The pathfinding-related variables of both patches and evacuees keep being updated every time step throughout each simulation run.

The basic schedule of the model is shown as follows:

I. The simulation begins with an initial simulation space where sets up by the observers, involving as series of pre-set environmental variables, such as the percentage of BNE agents, the number of evacuees, the width of exit, and other state variables. The type of moving combinations being observed as well as which kind of barriers placed are also selected at this step. It should be noted that all the environmental attributes remain constant throughout the entire simulation process.

II. The decision-making processes of evacuees deferring to different behavioural models (i.e. SR, RF and BNE) are conduced respectively during evacuation simulations. SR agents tend to follow the route with the shortest distance to the exit point. RF agents randomly choose a leader to follow, seeking to gather around the closest leader who knows the shortest exit route. BNE evacuees make inference about others' next actions and take the strategy considered to be the best responses to each other.

III. Agents adjust their moving directions (i.e. repeat patch-selection process) based on their own behavioural model every time step in response to the updated environmental conditions.

IV. Relevant state variables, plots, model views and interfaces are updated during the whole process of simulations.

2 Design Concepts

2.1 Theoretical Background

2.1.1 Bayesian Nash Equilibrium

Bayesian Nash Equilibrium (BNE) was introduced into this model as the underlying theory to better describe interactive decision-making process of rational and game-playing agents (evacuees). BNE provides a more comprehensive framework to analyze the interactions of strategies taken by different participants in such scenarios, and an approach to updating the probabilities of others' decisions based on real-time information obtained. Specifically, players in a game with incomplete information (e.g. Bayesian game) strive to maximize their own expected utility to achieve a Nash equilibrium, also called Bayesian Nash Equilibrium (BNE), where the strategies taken by players must be the optimal responses to each other [29, 33].

In this model, the rules of BNE are reflected as the probability distribution of nearby evacuees' next actions as well as a series of utility-related calculations, quantifying the interactive decision-making process of rational individuals in scenarios with varied environmental contexts.

2.2.2 Dijkstra's Algorithm

Dijkstra's algorithm is defined as a widely adopted graph searching algorithm for shortest wayfinding between the source node and all the others, with a shortest-path tree produced [48]. It was employed in this model as the fundamental theory to implement the individual decision-making process of agents using Shortest Route (SR) behavioral model.

2.2 Individual Decision-Making

In this model, decision-making process is simulated at an individual level and depends on the behavioral model (i.e. SR, RF and BNE) assigned to each evacuee.

SR evacuees. The decision-making logic of the evacuees using SR model is to find the evacuation routes with the shortest distance from their current locations to the exit points in the meantime with avoiding the barriers placed on their pathways.

RF evacuees. A certain number of RF evacuees are set as leaders, defaulting to 20% of the total, at the initial stage of simulations. The remaining evacuees randomly follow a leader in views, tending to gather around the closest leader who defers to SR model. Followers will find a new leader once the previous one is out of their sights, and this leader-finding process repeats until the end of the simulation.

BNE evacuees. An evacuee following BNE model determines his/her response to perceived surroundings in an integrated way considering both physical constrains (e.g. cognition map of evacuation space) and instant information (e.g. neighbors' movements). A set of utility-related calculations was conducted every time step to assist in path selection. Instead of a utility maximization approach in the initial implementation [28], some noise was introduced in this model to improve the decision-making logic of BNE agents to a multi-strategy combination: with 80% of agents choosing the path with highest U_{total}, 15% selecting the patch with second-highest U_{total}, and 5% choosing the third-highest U_{total}, to assist smart agents in taking the best responses to each other.

2.3 Individual Sensing

In this model, RF evacuees are able to sense the area in front of themselves within a cone of vision with a 60-degree viewing angle and an assigned vision distance. The value of this radius remains constant over each simulation run and could be adjusted by the corresponding slider *Radius*. BNE evacuees have capability to perceive ambient conditions in their Moore neighborhood and predict others' next moves.

2.4 Individual Prediction

BNE evacuees are capable to make inference about the congestion level of their surrounding areas at next time step by analyzing instant environmental information and the probabilities of their neighbors' next actions. That is, the expected comfort utility (U_{ec}) of each patch is estimated based on the explicit prediction of the movements of evacuees located on its Moore Neighbourhood as well as its comfort coefficient over a time step.

2.5 Interaction

Interactions among BNE evacuees are mediated by the variations of expected comfort utilities (U_{ec}) of the patches in their Moore neighbourhoods. In this model, the value of U_{ec} is associated with the expected number of evacuees who may move to this patch at the next time step, which in turn impacts the actual number of neighbouring agents. Evacuees following BNE model can adjust their directions after comparing the patch values of total utility (U_{total}) in their Moore neighbourhoods. That is, the current positions and expected next moves of evacuees influence the U_{ec} of patches, which in turn affects the next decisions of neighbouring evacuees.

2.6 Heterogeneity

In this model, the decision-making process of evacuees are heterogeneous depending on their allocated behavioral models. SR evacuees sought to select the shortest exit path in the meantime with avoiding the blockades placed on their pathways, with Dijkstra's searching algorithm underlying the design. The evacuees using RF model are divided into two groups: leaders and followers. The evacuation movements of RF leaders comply with the laws of SR model, and the remaining evacuees (i.e. followers) randomly choose a leader in views to follow, tending to gather around the closest leader who knows the shortest evacuation route. Followers will search another leader once the previous one is out of sight, and this leader-finding process repeats until the end of simulations. The evacuees following BNE model keep updating the probabilities of others' next moves in light of instant environmental information, and then adjust their moving directions based on the values of U_{total} in their neighbouring patches. The decision-making procedures mentioned above will take place in every time step until the agents evacuate successfully.

2.7 Stochasticity

Stochasticity has been introduced in three main mays in this model. Firstly, the model is initialized based on the environmental and agent settings assigned by the observer. Specifically, (a) initial locations of evacuees, (b) random allocations of evacuees' behavioral models, especially in BNE-SR/RF combinations, and (c) initial headings of evacuees are set to be randomly initialized in the model. Secondly, the decision making of an evacuee deferring to RF model is considered to be partly stochastic, as it is able to randomly choose a leader to follow when multiple leaders are in view, but the selection range is limited by its vision distance. Randomized decision-makings also exist in BNE evacuees: when facing over one neighboring patches with highest U_{total}, this BNE agent will randomly choose one to move.

2.8 Observation

The simulating performance of this BNE-informed ABM is indicated through two main measurements: evacuation time and pedestrian comfort level. Evacuation time has been recorded at the end of each simulation and the average U_{ec}, which is a mean value of all patches' U_{ec}, has been collected every time step over each simulation run, in order to better represent the average comfort level of individuals during evacuations in evacuation scenarios with varied environmental contexts.

3 Details

3.1 Implementation Details

The model was developed in NetLogo. The source code and experimental data are available at https://doi.org/10.25937/8bf3-h968.

3.2 Initialization

By default, the model was initialized with 2000 evacuees randomly scattering over the designated area on the one side of simulation space and presumed that all the agents (i.e. evacuees) can evacuate through the exit point with a width of 4 patches located on the right side. Agents were coded to navigate in varied constricted spatial environments in according to their assigned behavioral model (i.e. Shortest Route (SR) model, Random Follow (RF) model, or BNE model). Observers can regulate the initial settings of agents and evacuation space by assigning the total number of evacuees, the proportion of BNE evacuees, moving patterns, and so on through corresponding sliders. The movement combinations can be selected by the chooser *Moving-pattern* in which four patterns are available to choose from: Shortest Route (SR), Random Follow (RF), BNE mixed with SR, and BNE mixed with RF. In the first two patterns, all the evacuees are assigned the same behavioral model corresponding to which moving pattern was chosen. In RF pattern, the percentage of leaders who follows SR model defaults to 20% of the total and can be adjusted by the slider *Percent-of-RFleaders*. In the last two BNE combinations, the default percentage of BNE evacuees was set to 100% and the mixing proportions can be tuned as needed. In addition, to better observe the evacuation processes of evacuees following different behavioral models, each type of evacuees was assigned a specific color for distinguishing: SR evacuees are in green, RF evacuees are displayed in magenta while the leaders who follow SR model are still shown in green, and BNE evacuees are in orange.

The hypothetical evacuation space was made up of 1360 (68*20) patches where multi-occupations for each of them are allowed in this model, making it possible to explore whether and how this model can simulate emergent patterns of pedestrian behaviors in evacuation scenarios with different environmental contexts. The moving speed of each agent is tailored based on crowd density in surrounding area (i.e. the patch stayed and patches in its Moore neighborhood) and keeps updating every time step throughout each simulation run. The speed-density relation in this study is accordance with the Spatial-Grid Evacuation Model (SGEM) [44], and individual speed regulations depend on the reference speed assigned through the slider *Moving-speed* at model initialization with a default value of 1 patch per time step. The individual moving speed is inversely proportional to the number of neighboring evacuees, with full details in *Section 2.2.2 Speed Calibration*.

To further observe human emergent behaviors in high-density or life-threatening situations, this model implemented three types of barriers, which are *Horizontal Corridor*, *Vertical Corridors*, and *Random Squares*, standing for corridors, bottlenecks, and intersections respectively (see Fig. 3 in main text). The first one allows the placements of two oblong blockades with assigned size to form three narrow corridors so as to observe pedestrian dynamics in evacuation space with varied spatial constricted level. The second barrier mode consists of two vertical walls with an adjustable-wide gate separately. These two gates were placed at different locations, one is lower, and the other is upper, making it possible to capture individual behaviors when passing through cramped bottlenecks and narrow corridors. In the last type of barrier, several square blockades with adjustable size were placed randomly over the simulation space to explore the simulating performance of this model on pedestrian behaviors in evacuation scenarios containing intersections. Observers can select which type of barriers to set up by the chooser *Barriers-mode*.

3.3 Input data

So far, no input is read in this model.

3.4 Behavioral models for pedestrian decision-making

In this model, agent movements are determined by their allocated behavioral models. Three behavioral models have been implemented and described as follows.

3.4.1 Shortest Route (SR) model

Dijkstra's searching algorithm was adopted in this model to replace the weak SR strategy (i.e. choosing the path with shortest Euclidean distance between current location and exit point) in the initial implementation [49] to take into account congestion costs during evacuations. *Nw Extension*[4], a pre-bundled NetLogo tool adopted Dijkstra's algorithm as the underlying theory, was employed to describe individual decision process of SR agents through generating a network composed by mass nodes for path calculations. Agents (i.e. evacuees) following SR model strive to find the route with shortest distance to the exit in the meantime with avoiding the barriers on the way.

3.4.2 Random Follow (RF) model

The RF model designated a set number of agents, defaulting to 20% of the total, as the leaders at the beginning of simulations. Evacuation movements of RF leaders were in accord with the rules of SR model. The remaining agents (i.e. followers) randomly selected a leader in views (radius of view can be regulated through the slider *Radius*) to follow, inclined to gather around the nearest one to them. Followers will look for a new leader once the previous one was out of sight and this leader-finding process repeats till the end of simulation.

3.4.3 BNE behavioral model

Bayesian game theory was adopted in this study to describe the interactive decision-making process among rational and game-playing individuals. A set of mathematic expressions for utility calculations were introduced in this model to convert BNE theory into concrete decision-making rules. Since players in a Bayesian game make their decisions out-of-sequence, BNE evacuees in this model determine their next actions hinging on the values of *Total Utility* (U_{total}) for the patches in their Moore neighbourhood. The full details of the BNE model have been described in *Section 2.2.2*.

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[4] The complete documentation of *NetLogo NW extension* is available at https://github.com/NetLogo/NW-Extension.

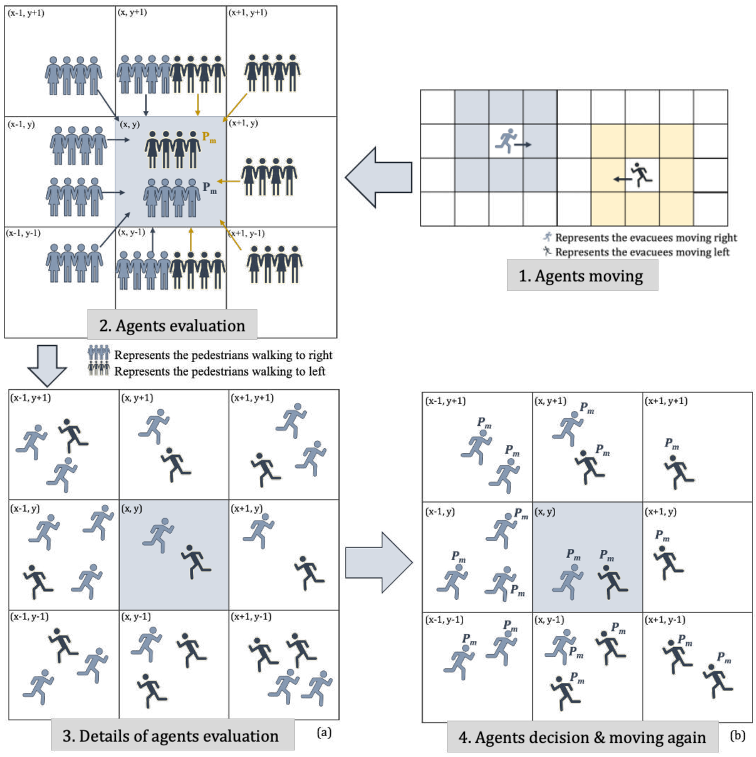

Figure B.2 The schema of decision-making process of the agents following BNE behavioral model

4 Simulation Experiments

4.1 Experimental Settings

A series of simulation experiments were conducted in three main scenarios: corridors, bottlenecks and intersections respectively using NetLogo BehaviorSpace. The experimental results were evaluated in terms of evacuation time and average U_{ec} to explore simulating performances of this BNE-informed ABM on emergent patterns of pedestrian evacuating behaviours. See Table S4 for an outline of all model inputs in each set of experiments.

Table B.4 The list of parameter settings in each set of experiments.

Parameters	**Values (Exp.1)**	**Values (Exp.2)**	**Values (Exp.3)**	**State**
Number-of-Evacuees	2000	2000	2000	Static
Moving-pattern	BNE mixed with SR/RF	BNE mixed with SR/RF	BNE mixed with SR/RF	Dynamic
Barriers-mode	Horizontal Corridors	Vertical Corridors	Random Squares	Static
Corridor-width	1, 2, 3, 4, 5.	1, 3, 5, 7, 9.	N/A	Dynamic
Barriers-side-length	N/A	N/A	11, 10, 9, 8, 7.	Dynamic
Percent-of-BNE-evacuees	0%~100% (+2%)	0%~100% (+2%)	0%~100% (+2%)	Dynamic

Probability-competing	50%	50%	50%	Static
Percent-of-RFleaders	20%	20%	20%	Static
Exit-width	4	4	4	Static
Radius	2	2	2	Static
Moving-speed	1.0	1.0	1.0	Static
Initial-position	15%	15%	15%	Static
weight-Ud	2.00	2.00	2.00	Static
weight-Uec	2.00	2.00	2.00	Static
Repetitions	50 simulations were conducted at each BNE percentage fraction (12750 runs in this set of experiments)	50 simulations were conducted at each BNE percentage fraction (12750 runs in this set of experiments)	50 simulations were conducted at each BNE percentage fraction (12750 runs in this set of experiments)	N/A
Values collected	Exit time; Average expected comfort utility	Exit time; Average expected comfort utility	Exit time; Average expected comfort utility	N/A

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