# Microscopic information processing and communication in crowd dynamics*

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## Abstract

Due, perhaps, to the historical division of crowd dynamics research into psychological and engineering approaches, microscopic crowd models have tended toward modelling simple interchangeable particles with an emphasis on the simulation of physical factors. Despite the fact that people have complex (non-panic) behaviours in crowd disasters, important human factors in crowd dynamics such as information discovery and processing, changing goals and communication have not yet been well integrated at the microscopic level. We use our Microscopic Human Factors methodology to fuse a microscopic simulation of these human factors with a popular microscopic crowd model. By tightly integrating human factors with the existing model we can study the effects on the physical domain (movement, force and crowd safety) when human behaviour (information processing and communication) is introduced.

In a large-room egress scenario with ample exits, information discovery and processing yields a crowd of non-interchangeable individuals who, despite close proximity, have different goals due to their different beliefs. This crowd heterogeneity leads to complex inter-particle interactions such as jamming transitions in open space; at high crowd energies, we found a freezing by heating effect (reminiscent of the disaster at Central Lenin Stadium in 1982) in which a barrier formation of naïve individuals trying to reach blocked exits prevented knowledgeable ones from exiting. Communication, when introduced, reduced this barrier formation, increasing both exit rates and crowd safety.

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## 1 Introduction

Crowds have typically been studied from two separate perspectives: the psychological perspective (in which human behavioural tendencies are considered in isolation from their physical embodiment and surroundings) and the engineering perspective (in which homogeneous driven particles interact on a purely physical basis). Although this dichotomy in approaches has long been criticised (e.g. [1]), established statistical-mechanical models of crowd dynamics (e.g. [2, 3]) have not yet addressed this issue; instead they traditionally justify simplistic particle behaviour through an assumption of panic (i.e. that people in crowd disasters behave irrationally, interchangeably and anti-socially). This assumption helps to justify a simplistic view of behaviour, such as when a crowd is compared to homogeneous particles like seeds or powders in a hopper [4]. People are not like homogeneous, interchangeable, non-rational, non-cognitive seeds in a hopper; in order to claim that our microscopic models represent crowds of people (and not of inanimate objects) we must begin to incorporate human factors into microscopic models.

The popular assumption that people generally panic in crowd situations is false (see [5, 6] for more on this point). By contrast, people are described as "at their best" in crowd disasters [7], in which they are seen to take decisions that make sense based on the information available to them at the time [8, 9]. Inadequate information, however, is known to be a factor in many crowd incidents. For example, Proulx and Sime have noted that, in fires, notification to occupants is often delayed — sometimes for fear of causing a 'panic' — resulting in precious minutes being wasted early in a situation. (This delay can itself contribute to disaster when not enough time remains for occupants to assimilate the information and move to exits.) Their experiments demonstrate that people require "information to define the situation and to take the decision to evacuate" [8].

The persistence of the noted dichotomy between physical and psychological approaches to understanding crowds means that microscopic models miss out on study of the physical effects of human behavioural factors. The purpose of this article is to begin to bridge this gap in the case of two behavioural factors — information processing and communication — in the context of our force-enabled version of the floor field pedestrian model [2, 10]. In developing our simulation, we shall retain the particle-based metaphor common to microscopic models, but apply a novel approach to modelling human factors: the Microscopic Human Factors methodology, which guides the implementation of our two behavioural factors at the heart of the existing model. We shall add spatial information discovery to the modelled environment, and examine both qualitative and quantitative effects at the crowd level that result from information processing by particles. We then activate communication between individual particles and analyse the changes in microscopic crowd dynamics due to this social behaviour. In discussion, we shall relate our results to a classical crowd disaster (Central Lenin Stadium), then conclude.

# 2 Simulating information processing and communication

We have developed the Microscopic Human Factors (MHF) methodology [6, 11], which is designed to provide guidance in creating a microscopic simulation of human behaviour that is *tightly integrated* with a microscopic model at an appropriate level of abstraction. The MHF methodology requires three complete and increasingly abstract descriptions of information processing and communication in crowds: (i) the *specification* circumscribes the behaviour to be modelled and identifies the theoretical stance toward the macroscopic emergent behaviour, (ii) the *reduction* expresses formalism-neutral rules that guide individual particles in microscopically generating the emergent behaviour, and (iii) the *implementation* describes the integration of these rules with the formalism of a particular microscopic model. A simulation missing one of these levels of description is incomplete (as an explanation of behaviour) due to a failure, respectively: (i) to explain the relevance of the model to our understanding of crowd dynamics, (ii) to explain which parts of the simulation are theoretically relevant vs. formalism artifacts, or (iii) to demonstrate how the results may be influenced by the formalism selected.

## 2.1 Specification

Our conception of information processing is due to Sime's observation that:

> It is important to note that a building or setting (such as an underground station) is not only a physical space or structure, but *an information system through which people move*. If this is remembered, it should help direct attention to the perspective of crowd members, as well as to the physical dimensions of a setting (i.e. psychological and engineering parameters) [1] (emphasis Sime's).

Sime describes a system with three domains: occupants, space and information. This implies a system with distributed artifacts (e.g. signs, doorways, etc.) that are able to impart knowledge if perceived. Agents must move through the space to within perceptual range of the artifact to gain the knowledge.

That people can extract information from their environment implies a heterogeneous crowd: two people close to one another may be engaged in different actions due to their personal history of information gathering. To a person with more complete knowledge, the space affords more (or more accurate) options in terms of movement goals. In exiting a space, a more knowledgeable person may move differently (e.g. toward little-known exits) from others close to them, a difference explained by their extra knowledge. During the Cocoanut Grove bar fire, for example, some occupants of a packed basement lounge reached safety (led by knowledgeable staff) through a hidden emergency exit while many others died trying to escape up the main entrance stairwell [12].

People moving through a space are sensitive to new information and can readily absorb it and change their behaviour accordingly. For example, upon approaching a blocked exit, a person wishing to leave changes their behaviour (e.g. moving instead to an alternate exit). Similarly, a person discovering a previously unknown open exit will assimilate this information leading to the potential for its use [13]. (It should be noted that this premise, in particular during an evacuation, is contradictory to the hypothesis that people panic. It depends on a view of people as rational and capable of cognitive processing.)

It is not only inanimate aspects of a scenario that can carry information. People moving through a space occupied by others are capable of socially sharing their knowledge of the space through communication (as in the Cocoanut Grove example). Johnson has reported that generalised shouting was futile in a crowd disaster [7], so when crowd members communicate amongst themselves (as opposed to, say, amplified overhead announcements by crowd managers) we focus on person-to-person communication.

We can use the three described domains as a guide in developing our simulation. Microscopic models, as noted, already have a strength in physical modelling. We shall explicitly introduce the information domain into the model. We shall augment the occupant domain to better model the basic human ability to process and respond to information during circulation. The desired outcome is improved model relevance to real people and scenarios. We have not attempted to model all aspects of information in crowds; for example, issues of trust in communication and exit preference are not captured by this model. Our goal here is to begin an investigation of information processing and communication in crowds, and we leave interesting factors such as these to future work.

## 2.2 Reduction

Having explained the importance of information and how it is obtained, used and communicated in crowds, we turn now to a discussion of how this process can be explained through formalism-neutral rules that guide individual crowd members. We focus on diverging movement goals as the end result of information accumulation by individuals within the crowd. These divergent goals will arise from evolution of the beliefs of individuals, caused by discovery and communication of new spatial facts. The ultimate source of these facts will be an information system incorporated at the heart of a microscopic movement model. From the specification above, we derive the following essential, and individual rules:

**Explicit mental content.** The key to generating a heterogeneous model based on discovery and communication of spatial knowledge is to note that different individuals have differing mental content about their environment. In a microscopic model we aim for simplicity and abstraction; we want to avoid complicating the model with, for example, inductive or deductive reasoning, or large formal knowledge representation systems (e.g. [14]). In order to determine the effects of — and interactions between — different beliefs on behaviour, it is desirable that the set of possible beliefs be restricted in size. Thus, our model maintains certain specified and indivisible views of the world, and individuals select from among these views during model execution. In a simulation, these views are created by the modeller as part of specifying the scenario. For example, the modeller may wish to represent one view of the world in which existence of a set of exits is unknown, and a second in which the exits are known; this could underlie two different behaviours, depending on which view of the world an individual considers.

**Discovery and accumulation of knowledge.** Individuals accumulate information about their surroundings as they move throughout a space. This discovery is triggered upon moving to particular circumscribed areas within the model, whose size and placement is consistent with the modeller's intentions with respect to the perceptual capabilities of crowd members being modelled. Discovery of information corresponds to changing mental content as described above. Like the mental content itself, the discovery areas are specified by the modeller, who may choose to allow these discovery zones to be somewhat dynamic; this allows representation of information that becomes available at certain locations after the start of the simulation (e.g. localised announcements).

Individuals accumulate knowledge over time while moving through spaces. Learning some facts about the world does not preclude additional facts being learnt later, and later learning generally accumulates with — as opposed to supplanting — previous mental content. To some extent this rule is already addressed by the set of indivisible mental content, which requires the modeller to specify all possible views of the world. The present rule, however, goes further by requiring the provision of acceptable transition rules. For example, a person discovering that an exit is blocked will not generally regress to a state in which they have forgotten the blockage. (This is not to say that misinformation cannot occur. Someone can learn of a putative exit and subsequently learn that the exit does not exist. In this case it is not that they have regressed to an earlier state of knowledge through simple forgetting.)

**Directed communication.** By simulating direct communication we can use the model to investigate behaviour engendered by people becoming informed, including misinformed, without physically visiting the discovery locations. As noted in the specification, the communication model is assumed to rely on direct person-to-person contact. We take communication to occur not on a random basis, but with a purpose, namely to assist in achieving movement goals when blocked by another individual. (Other possible purposes for communication, for example local leadership and altruism, are left for future work.)

## 2.3 Implementation: Floor field model

Before explaining the implementation of the rules just described, it is important to describe the formalism within which these rules will be expressed. We have found the floor field model cellular automaton [2] to be an excellent formalism for implementing MHF models, affording close fusion between the model's implementation and new rules representing human behaviour. This model has proven to be full of potential, and has been the subject of a number of interesting refinements and extensions (e.g. [6, 10, 15–25]); it is necessary to select a point in time that serves as a baseline for our work. We adopted the model as it was presented in an exploration of the floor field model's applicability to egress simulation [16]. We have elsewhere described our interpretation of this model as a multi-agent system and our additions of pushing (force initiation), leaning (force re-transmission) and crowd safety simulations [6, 10]. Accordingly, we here present a brief explanation of the floor field model sufficient to explain in section 2.4 how we have implemented an information system with communication amongst floor field pedestrian particles.

The floor field model, according to our force-enabled agent-based restatement, is a microscopic crowd model of individuals (agents) with two actions: moving and pushing. Agents are initially distributed at random on a 2-dimensional grid that provides a co-ordinate system, both for movement and for maps of information available to agents called fields. Agents have an individual rule-based behaviour, balancing their movement decisions between reducing distance from desired goals and following other nearby agents. The floor field model as originally specified does not provide for individual cognition beyond combining the two perceptions just described.

### 2.3.1 Physical environment

**Cells and occupancy.** The discrete time evolution of the model considers the dynamic and unfolding occupancy of cells. Agents move a distance of zero or one cell per time step. Movements are planned by all agents in parallel, then executed simultaneously. Up to one agent can occupy a cell per time step. Certain cells within the space (e.g. around the perimeter of the modelled area) can be designated as wall cells. These cells are unavailable for occupation.

**Cell adjacency.** The model uses the Cartesian directions in determining cell adjacency. In other words, allowable movement directions on the two-dimensional grid are North, South, East and West. (It is often required to speak of the possible cells an agent could move to in the next time step. This is called the *neighbourhood* and, in the force-enabled floor field model, includes the four adjacent cells.)

### 2.3.2 Floor fields

Agents make observations of their local environment by consulting one of three *floor fields*, and in some cases alter these fields as they move through the simulated space. Each field provides a measure of a specific type of information, detailed below. (Traditionally in the floor field model, the fields were composed of "bosons" which interacted with and drove the agent particles, dubbed "fermions" [2]. We prefer now to refer, where required, to virtual "particles" on cells as the constituents of these fields.) Aside from the presence of wall cells or other agents in the neighbourhood, agents do not have recourse to any information aside from the fields.

**Static field.** The first of the three fields provided by the model is the continuous *static field*, the strength of which varies inversely with the distance to the exit (see figure 1a). During egress, the static field can be considered a measure of desirability; cells closer to an exit are more desirable. As expected from the name, the static field is fixed from the start of the simulation run, and does not change during the run. Any one of several methods can be used to calculate the value of the static field, with different simulation dynamics resulting [18, 24]. We adopt the simple linear distance measure used by [16]:

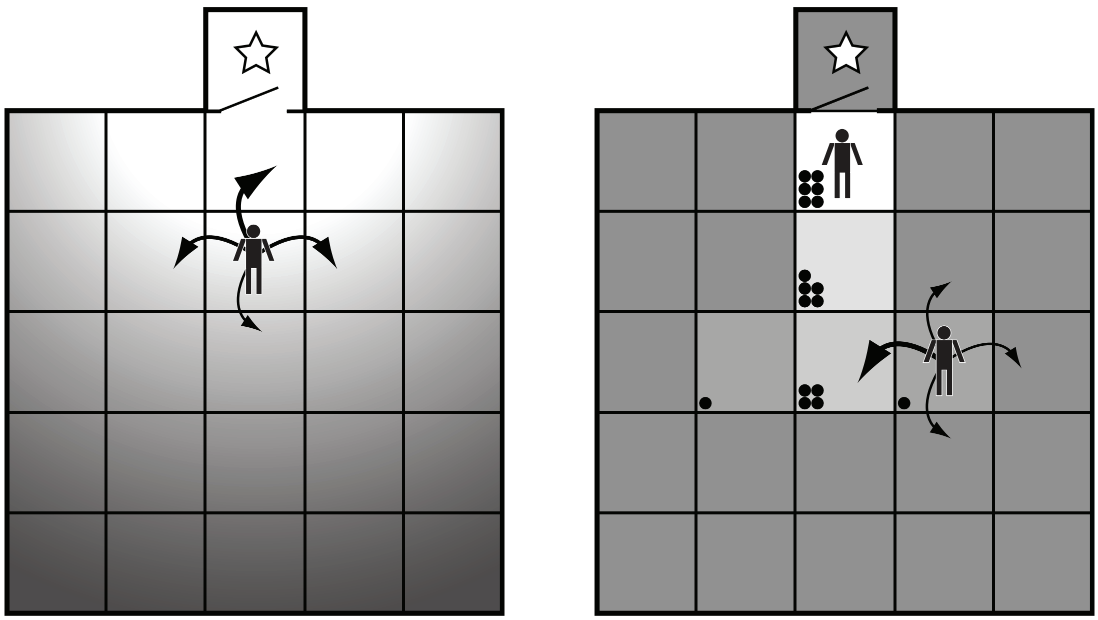
$$s(i,j) = \min_{(d_x,d_y)\in X} \sqrt{(d_x - i)^2 + (d_y - j)^2} \tag{1}$$

$$s_{max} = \max_{\forall(i,j)} s(i,j) \tag{2}$$

$$S_{ij} = s_{max} - s(i,j) \tag{3}$$

Here $s(i,j)$ gives the distance from a cell with coordinates $(i,j)$ to the closest exit in $X$, the set of coordinates of all exits. The normalisation number, $s_{max}$, is the greatest distance to an exit from any cell. The final static field value, $S_{ij}$, decreases from $s_{max}$ at exit cells to 0 on the furthest cell from an exit.

**Dynamic field.** The second of the two fields provided by the floor field model is the *dynamic field*. It provides for agents to become aware of the movement of others by analogy with ant pheromone chemotaxis (c.f. [26]), reducing long-range interactions to local ones. It is a discrete field. When an agent moves from a cell $(i,j)$ to an adjacent cell it drops a dynamic particle on the origin cell ($D_{ij} \to D_{ij} + 1$) (see figure 1b).



**a.** Floor field model space with static field, $S$. Agent (*pictured*) can move to neighbouring cells (*arrows*) or current cell (*arrow not shown*). Cell selection is probabilistic based on agent's perceived desirability of cell (*arrow size*). Movement to exit cell (*starred*) results in subsequent disappearance of agent. Static field (*colour gradient*) represents inherent cell desirability; field strength on own and neighbouring cells is accessible to the agent.

**b.** Floor field model space with dynamic field, $D$. Previous agents (e.g. *top agent moving up from centre*) have dropped dynamic particles (*circles*). Dynamic particles probabilistically decay (*middle group*) or diffuse to neighbouring cells (*lower group*). An agent attending only to the dynamic field uses this particle density like a trail (*lower agent following colour gradient*) to follow preceding agents.

**Figure 1:** Static (a) and dynamic (b) floor fields in the floor field model [2]

The dynamic field is so named because — in contrast to the static field — its particles are considered to be active; like a scent, the dynamic field decays and diffuses. During each time step, each dynamic particle in the model decays with probability $\delta$. Those particles that do not decay may diffuse (move to a randomly selected adjacent cell) with probability $\alpha$. (Both of these probabilities are parameters to the model.) Agents can consult the values of the dynamic field in neighbour cells in order to follow virtual "paths" left by previous agents. Due to the effect of $\delta$, paths must be constantly refreshed in order to be effective at guiding pedestrians, while $\alpha$ controls the spreading of these paths (with the effect of recruiting nearby agents to the path).

**Force field.** The third field, introduced in [10], contains unit vector particles representing directed units of force. The total force on a cell $(i, j)$ is $\vec{f}_{ij}$, the vector sum of the vector particles present there. (The force on cells is initially zero.) In real crowds, forces are retransmitted from person to person through "a domino effect of people leaning against each other" [27] and thus, in each time step, $\vec{f}_{ij}$ is propagated in its entirety by distributing $|\vec{f}_{ij}|$ force particles to the neighbouring cell in the direction of $\vec{f}_{ij}$.[1] Force is dissipated (i.e. its underlying particles disappear) if it would move onto an empty cell or a wall cell, or a cell with an injured agent (see below).

### 2.3.3 Cell selection and movement

To guide agents through the model, a score, $c_{ij}$, is assigned to each cell indicating its desirability:

$$c_{ij} = \exp(k_D D_{ij}) \exp(k_S S_{ij}) (1 - \eta_{ij}) \, \xi_{ij} \tag{4}$$

Here, $\eta_{ij}$ is 0.5 for occupied cells (otherwise 0) and $\xi_{ij}$ is 0 for walls (otherwise 1).

Two sensitivity parameters, $k_S$ and $k_D$ are provided as parameters to the model, as it is desirable to regulate the information available to the agent from each of the floor fields. (It may be that the agents do not have perfect information concerning the movement of others, for example due to darkness.) The $k_S$ and $k_D$ parameters scale the influence of $S_{ij}$ and $D_{ij}$ (the static and dynamic field values, respectively); a sensitivity parameter can increase a field's influence ($k > 1$) or decrease it ($0 \leqslant k < 1$). To take an egress example, if $k_S$ is low, then the agent moves through the grid ignorant of where the exits are. If $k_S$ is high, then the agent is attuned to the location of exits. If $k_D$ is low, then the agent is not concerned/aware of the movements of others. If $k_D$ is high then the agent will be disposed to follow other agents through the grid.

Agents engaged in selection of a target cell for movement convert the scores on neighbouring cells to probabilities, according to equation 5, in which $N$ is the set of co-ordinates of neighbour cells.

$$p_{ij} = \frac{c_{ij}}{\sum_{(i',j') \in N} c_{i'j'}} \tag{5}$$

All agents probabilistically select cells in every time step, simultaneously, and before any movement occurs. Movement is not always possible (providing an implicit chance of remaining still) either due to selection of a cell that is not vacant or is desired by more than one agent. (In the latter case a random agent is successful.) In either case, an agent frustrated in movement will push, generating force by dropping $\rho$ force vector particles (a value that depends on the strength of the agent) oriented in the direction of desired travel onto the desired cell.

For the purpose of modelling ingress or egress behaviours, the floor field model permits designated exit cells, generally within the walls. Agents move onto these cells as usual and occupy them for the duration of the time step. The next move of an agent occupying an exit cell is to disappear from the model.

### 2.3.4 Effects of force

Force can have serious consequences for agents. Although the vector sum of opposing forces may cancel to zero on a cell, an agent occupying that cell is considered to be pinned between these forces. For this reason, when considering effects on agents, the scalar sum $f_{ij}$ of force vector particles is used, rather than the vector sum $\vec{f}_{ij}$.

Two thresholds are provided for agent force consequences: With moderate force ($f_{ij} > \chi$) agents lose control of their own movements, bypass the cell selection algorithm of section 2.3.3, and are instead forced to select the cell in the direction of $\vec{f}_{ij}$. With extreme force ($f_{ij} > \phi > \chi$) the agent is injured, becomes totally inactive, no longer moves through the model, and is treated like a wall cell by other agents and the force propagation algorithm.

[1] In the case where $\vec{f}_{ij}$ points between two cells, a probabilistic quantisation is used where each of the $|\vec{f}_{ij}|$ particles deposited has a chance of being deposited on one of the two cells according to

$$1 - p_a = \frac{\hat{f}_{ij} \mod 90}{90} = p_b$$

where $p_a$ is the probability of selecting the neighbour with the lower angle, $p_b$ is the probability of selecting the neighbour with the higher angle, and $\hat{f}_{ij}$ is the angle of $\vec{f}_{ij}$ expressed in degrees.

### 2.4 Implementation: Human factors

We can now proceed to fuse the individual rules for information processing and communication (section 2.2) with the existing individual rules of the floor field model (section 2.3).

#### 2.4.1 Representations of space

The changes to the model depart from the force-enabled floor field model in two major respects. First, they allow for individual agents to perceive the modelled world differently from one another, creating a heterogeneous crowd. Second, they allow for agents to change their view of the world, either under the influence of a new discovery field, or through a simple inter-agent communication mechanism.

In the floor field model, the individual's only representation of space is the static field, which encodes a distance from points of interest. In the new model, the reduction requires that the modeller make explicit all the possible views of the world. In order to represent multiple views of the world within the floor field model, we replace its single static field with a set of static fields. Each possible view of the world is represented as a distinct field within this set, and each represents an indivisible and complete view of the space.

We redefine the symbol $S$ to refer to a set of static fields rather than the sole static field of the floor field model:

$$S = \{S_0, S_1, S_2, \ldots, S_n\} \tag{6}$$

The semantics of the static fields are not altered from the original model. Each of the fields is created from a set of points of interest using one of several metrics [18,24] to determine the distance from each cell to the nearest such point. When modelling egress with the classic floor field model, we take the set of locations of interest to be the same as the set of exit cells in creation of a single static field; in the present reformulation, the additional static fields would typically include points of interest at locations other than at real exits (representing blocked exits, or misinformation) and/or would exclude points of interest at legitimate exits (representing exits that are unknown to an agent having that view of the world). For example, a static field incorporating belief in a non-existent (or blocked) exit would be calculated by supposing the presence of that exit and then carrying out the standard method for calculating the static field.

Having provided for multiple representations of the world, the agents must be modified to allow them to determine which representation is currently being consulted. Each agent is extended by adding an integer index into the set of static fields called the view selector, $\psi$. The view selector identifies the static field currently being consulted by the agent, which has no access to the information in other static fields.

The cell scoring function of the model (equation 4) is altered to take account of the view selector:

$$c_{ij} = \exp(k_D D_{ij}) \exp(k_S S_{\psi ij}) (1 - \eta_{ij}) \, \xi_{ij} \tag{7}$$

Notice that in equation 7 the term $S_{\psi ij}$ replaces $S_{ij}$, reflecting the alteration in meaning of $S$ due to equation 6. In the original floor field model the value $c_{ij}$ conceptually exists independently of an observer, while in the new model it is dependent on an observer (who sets the value of $\psi$).

Equations 6 and 7 together represent the primary change made to the floor field model to support heterogeneous crowds based on knowledge of space. By providing a spatial representation at an appropriate scale — tightly integrated at the heart of the floor field model — we maintain the causal connection between these rules and the emergent crowd behaviours of the floor field model.

#### 2.4.2 Physical discovery of spatial information

As the agent moves through the space it is necessary to provide for a mechanism that allows the agent to discover information, changing its beliefs about the world by updating its $\psi$ attribute. The reduction provides for a spatial mechanism that identifies certain circumscribed areas as zones of detection for new spatial information.

In the ontology of the floor field model, the way to distribute information spatially is with floor fields, and the unit of resolution of all spatial information is the cell. This suggests a new field to manage discovery. Accordingly, we define a new floor field called the *discovery field*, $I$, in which the value on each cell $(i, j)$ is an integer $0 \leqslant I_{ij} < |S|$ specifying the view selector that an encountering agent should adopt.[2] Encountering a cell $(i, j)$ on which $I_{ij} \neq \psi$, implies a potential change to $\psi$ to bring it in line with $I_{ij}$ (see figure 2).

As described in the reduction, when encountering $\psi'$, a new index into $S$ from the discovery field, agents must determine if this transition is allowed. This prevents agents from regressing when leaving information areas. (For example, in figure 2, if the agent steps to the west, into the area with $I_{ij} = 1$ we want $\psi$ to become 1. If the agent subsequently steps east, we do not want $\psi$ to return to 0, as this would imply forgetting.) We have adopted a finite-state machine approach to this problem, specifying the allowable transitions $\psi \rightarrow \psi'$. For

[2] The symbol $I$ (for information) is used as $D$ already indicates the dynamic field.

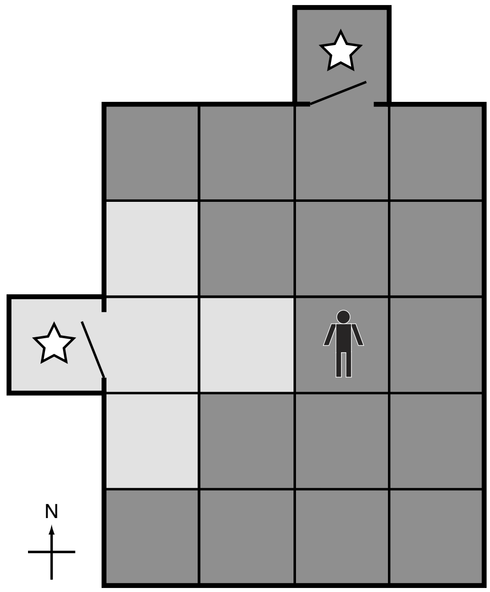



**Figure 2:** Discovery field, $I$, showing a proximity effect in which approach to a previously unknown exit leads to discovery. In this example, the discovery field encodes two potential view selector values: 0 *(dark cells)* or 1 *(light cells)*. These are potential agent $\psi$ values (indices into the set $S$ of static fields). Suppose that $S_0$ identifies distance only to the north exit, $S_1$ identifies distance to the closest exit and that the agent's $\psi = 0$. (In this state of affairs, the agent, despite being equidistant from both exits, is ignorant of the western one.) A westward step, into the region where $I = 1$, will cause the agent to learn of the western exit (through update of $\psi = 1$ and hence consultation of $S_1$). Any other step, by contrast, leads to no new knowledge (continued $\psi = 0$ and consultation of $S_0$). The agent can never exit west having $\psi = 0$; due to probabilistic cell selection, however, the agent may exit north with or without knowledge of the western exit (i.e. with $\psi \in \{0, 1\}$).

the purposes of this article it is sufficient to enforce a very simple transition rule: $\psi$ can only increase monotonically:

$$\psi = \begin{cases} \psi' & \text{if } \psi < \psi', \\ \psi & \text{if } \psi \geqslant \psi' \end{cases} \tag{8}$$

According to this transition rule we order static fields in the set in order of increasing knowledge. In a two field scenario, for example, agents may initially believe there are two exits in the space, but upon attempting to use one of the exits discover it blocked. The former view represents a more naïve view and accordingly appears earlier in the set than the latter.

While convenient to the purposes of this article, the model is not limited to a monotonic arrangement of fields. Any logical state transition rule — including enumeration of valid transitions — can be used. What is important is that values of the discovery field logically represent the minimum information available to an agent in that location, with $\psi$ taking on the discovery field value of the local cell only if it represents an increase in knowledge.

#### 2.4.3 Communication of spatial knowledge

Agents encountering one another can communicate spatial information. There is no prototype for this within the floor field model, so our direct communication model is a new development. Communication requires both a trigger condition, and a mechanism for information transfer.

The reduction specifies that communication serves a purpose, namely to assist in achieving movement goals. In selecting a trigger for communication, then, we note a similarity with the trigger for voluntary force application: Both communication and pushing are attempts to get a conflicting agent to adopt a more beneficial movement pattern. We assume that communication, therefore, will occur exactly in the same situations in which the agent applies a pushing force; when movement is frustrated due to an occupying agent on the agent's desired cell the agent will communicate as well as push.

Like pushing, communication is a directed activity from one agent toward another. Accordingly, a stigmergic mechanism involving an omnidirectional field is a less desirable implementation compared to a more specific mechanism isolated to the two agents. Our implementation involves a direct message from a communicating agent to a blocking agent. Communication in this sense means sharing information in order to cause the blocking agent to be recruited to the communicating agent's goals; the communicating agent shares its view of the world with the blocking agent. As agents' view of the world is represented by the $\psi$ attribute, communication is implemented by updating the $\psi$ parameter of the blocking agent. Like the discovery mechanism, communication is for information gain; accordingly, equation 8 is again used to prevent communication-induced forgetting. The blocking agent makes use of the updated $\psi$ parameter on the next time step.

#### 2.4.4 Algorithm

Algorithm 1 shows a single time step of the resulting simulation, capturing the ordering of the steps just described and their simulated parallel update. In the STEP procedure, lines 4–5 show the effect of obtaining the current view selector and using it for cell selection. Lines 9–10 of STEP provide the mechanism for discovering information (by consulting the discovery field, $I$, when moving to a new location) and for communicating to others (at the same time as force is delivered).

# 3 Results

Three scenarios are presented in order to demonstrate the effects of introducing information discovery, processing and communication into the model. First, we present a baseline scenario to show how the force-enabled floor field model performs without any divergent movement goals. Second, we introduce information discovery and processing. Finally, we enable communication.

Like the scenarios studied in previous floor field model egress studies [6,10,16], scenarios take place in a room of dimension $61 \times 61$ cells, surrounded by wall cells. Because we are less interested in bottlenecks and more interested in a crowd that moves enough to allow interactions between groups of agents, we here provide for many more exits than in previous studies. Accordingly, one wall of the room contains 10 exits, each of width 3 cells, spaced evenly along the wall (see figure 3). For $k_S$ and $k_D$, we have followed previous work [10] in selecting three levels of agent drive defined as: low $(k_D, k_S) = (10, 0.4)$, medium $(k_D, k_S) = (4, 1)$ and high $(k_D, k_S) = (0, 7)$. (As our interest here is not in the effects of extreme force at bottlenecks but rather in agent interactions, we here selected $k_S = 7$ rather than $k_S = 10$ at high drive; the present value still produces relatively high drive, but largely eliminates the aisle effect at bottlenecks — c.f. [6,10].) There were 1116 agents at the outset of the simulation (30% occupancy). Agent pushing forces ($\rho$) were drawn from a normal distribution (mean 5, standard deviation 1). Remaining parameters are as follows: $\alpha = 0.3$, $\delta = 0.3$, $\chi = 3\rho$. All runs were repeated 50 times and mean results are reported.

We will report on three dependent measures: number of agents exiting in a fixed interval (350 time steps, to allow comparison with results of [10]), number of agents injured during the simulation and number of steps taken by exiting agents (quantification of directness of agent exit). Not all agents are able to exit in every case, either because the number of time steps available is limited or because agents become injured.

As described in section 1, actions taken in crowd situations are best viewed in the light of the information available to the individual at the time. Indeed, disaster investigations often include questionnaire studies in which survivors are asked where and when they noticed danger cues and became aware of key facts (e.g. [28]); this information is of great interest in understanding behaviour. Accordingly, in the results reported here, we have often grouped agents based on $\psi$ upon exit. This allows us to report how many agents in each information state were successful in exiting as well as how directly these agents moved toward the doors.

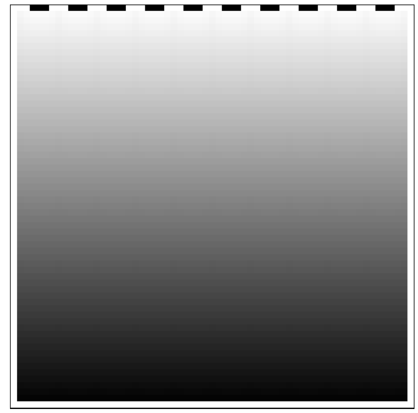


**Figure 3:** Physical environment for model scenarios. Ten exits shown (*black cells in walls*) with static field (*colour gradient*). Agents not shown.

Although looking at the differences across groups is one way to determine the heterogeneity of the crowd, observation is key to understanding the behaviour of a heterogeneous crowd. In studying only exiting agents we would naturally leave out agents who do not exit the space; analysis of the non-exiting agents is made more complex due to the fact that their failure to exit is sometimes produced by interactions between the groups. We will discuss the non-exiting agents by recourse to observation.

## 3.1 Homogeneous crowd

As a baseline, this first scenario contains only one static field that correctly identifies the locations of all the exit cells (see figure 3). All values of the discovery field indicate the use of this single static field, and all agents consult this static field from the outset of the simulation.

In previous work we have found that moderate drive to exit produces the best exit rate [6,10]. Although one might predict that providing additional exits would accommodate more urgent egress, we found a continued advantage for moderate exit drive (figure 4). (For each value of $\phi$, we compared the number of exits at high and medium drive with standard Welch's $t$-tests [29]; each comparison was statistically significant with two-tailed $p < 0.001$.)

The results of this scenario, however, differ from previous scenarios studied [10] in that injuries — even when numerous (at high drive with low injury thresh-

```
PROCEDURE STEP(D, S, F, I, agents)
 1  DECAY-AND-DIFFUSE(D)
 2  for each a in agents
 3       do a.CHECK-INJURY(F)
 4           ψ ← a.GET-VIEW-SELECTOR()
 5           a.CELL-SELECT-WITH-FORCE(D, S_ψ, F)
 6  for each a in SHUFFLE(agents)
 7       do if a.ATTEMPT-MOVE() = FALSE
 8             then a.PUSH()
 9                  a.TELL(ψ)
10             else  a.DISCOVER(I)
11  PROPAGATE-FORCE(F)

PROPAGATE-FORCE(F)
1  for each (i, j) in F
2       do if IS-EMPTY(i, j) or IS-INJURY-AT(i, j)
3             then ▷ force is not propagated
4             else  for n ← 1 to floor(|f⃗_ij|)
5                         do (i′, j′) ← CELL-IN-DIRECTION(f̂_ij, i, j)
6                            if not IS-EMPTY(i′, j′)
7                               then DROP-FORCE-PARTICLE(F′, i′, j′, i, j)
8  F ← F′

AGENT METHOD TELL(ψ)
1  s ← SELF
2  (i, j) ← s.GET-DESIRED-CELL()
3  r ← AGENT-AT(i, j)
4  r.HEAR(ψ)

AGENT METHOD DISCOVER(I)
1  s ← SELF
2  (i, j) ← s.CURRENT-LOCATION()
3  s.HEAR(I_ij)

AGENT METHOD HEAR(ψ′)
1  s ← SELF
2  ψ ← a.GET-VIEW-SELECTOR()
3  if ψ′ > ψ
4     then s.SET-VIEW-SELECTOR(ψ′)          ▷ New view selector not used until next step
```

**Algorithm 1:** Force-enabled floor field model step function modified for information processing and communication. The following procedures have been described elsewhere [6] and their definition is not relevant for our purposes here: DECAY-AND-DIFFUSE that implements the dynamic field propagation discussed in section 2.3.2, CHECK-INJURY that marks the agent as injured if $f_{ij} > \phi$, CELL-SELECT-WITH-FORCE that causes an agent to select (or be forced to select) a target cell for movement, ATTEMPT-MOVE that moves the agent and returns true (or returns false if movement is blocked). The functions PUSH (drop force particles on $a$'s current cell, which will be propagated to $a$'s desired cell at STEP line 11), GET-VIEW-SELECTOR and SET-VIEW-SELECTOR (access $\psi$ of agent), GET-DESIRED-CELL (return the currently selected cell), AGENT-AT (return a reference to the agent at a particular location), CURRENT-LOCATION (return the current position of the agent) and SHUFFLE (randomly re-order a list) are considered primitive and their implementation is not shown.

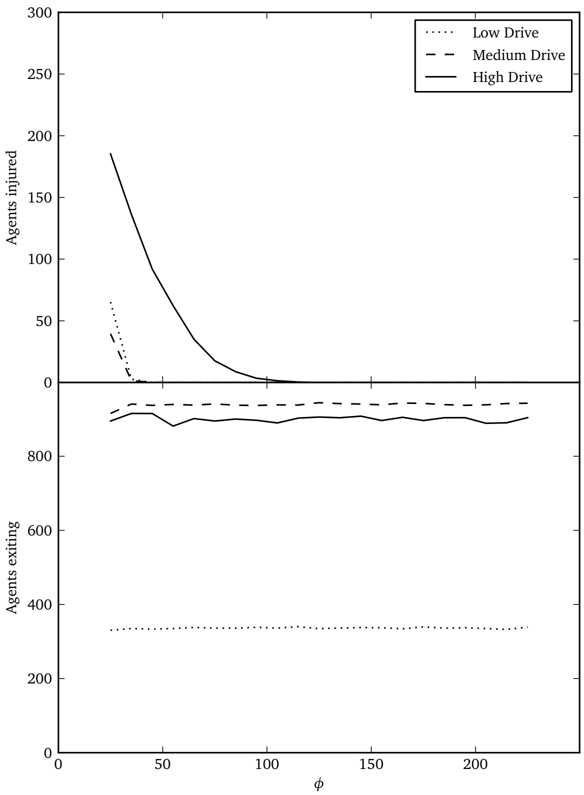
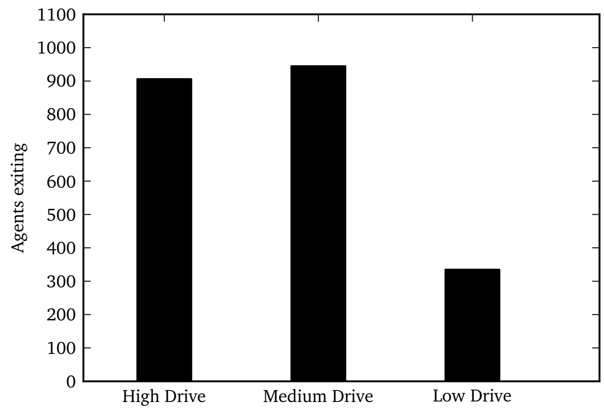
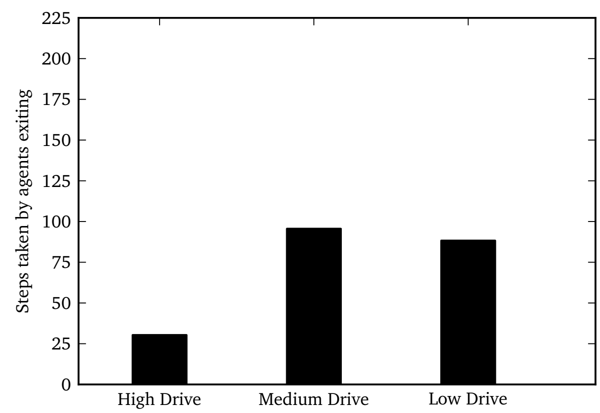



**Figure 4:** Homogeneous crowd: Agents exiting and injured. Range of $\phi$ explored.




**a.** number exiting.




**b.** steps taken by agents exiting.

**Figure 5:** Homogenous crowd: Agent egress measures. ($\phi$ = 125)

olds) — did not have a pronounced effect on the exit rate. Here the large numbers of exit cells reduce the tendency of injured agents to physically prevent egress through blockage of the exits. For this reason, in the remainder of this article we will not analyse the effects of injury threshold on agent exits, instead we will fix $\phi = 125$ (the mid-point of the explored range), and show exit results as in figure 5a.

Let us consider figure 5b, the number of steps taken by agents at differing crowd densities. At high drive, the mean number of steps to exit is 30.36, very close to the 30.5 that would be expected for a complete optimal exit given a uniform distribution in a space of size $61 \times 61$. The larger number of steps in the remaining two cases indicates a more circuitous route followed due to the influence of the larger $k_D$ parameter, and consequent smaller influence of the static field. At medium drive, almost all the agents were able to exit, but many more steps were taken. At low drive, agents are not motivated to move toward exits, and so many fewer agents exit — primarily those initially located close to the doors; even if initially close to the exits, exiting agents take large numbers of steps to do so.

We have established baseline results for our scenario with ample exit cells, and only a true static field. Agents are relatively unimpeded in exiting. Let us now turn to the question of information discovery and information processing. How would crowd dynamics be altered if agents believed in a second set of exits?

## 3.2 Heterogeneous crowd

This scenario takes place in the same physical space as the previous scenario. This scenario, however, contains two static fields. The first static field (figure 6), used by all agents at the outset of the simulation, reflects all of the real exits, but also supposes an identical set of exits on the opposite wall (which are in fact blocked). The discovery field is configured so that agents approaching the blocked exits (i.e. coming within two cells of the wall with the blocked exits) switch to the second static field, which only reflects the good exits (figure 3). For the purpose of characterising the effects of varying beliefs alone, we here disable the communication be-

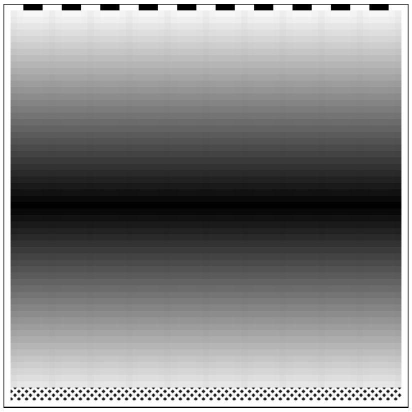


**Figure 6:** Static and discovery fields in the heterogeneous scenario. All agents start with the static field shown ($S_0$). The crosshatched area indicates the two cells nearest the wall in which the discovery field value is 1. Agents moving onto these cells change to the second static field ($S_1$), which is identical to the one displayed in figure 3.

**Figure 7:** Three groups of agents at discovery of blocked exits. Naïve agents exiting northwards *(group 1)*. Note barrier formation as knowledgeable agents at the south wall *(group 2, in white)* cannot pass southbound naïve agents *(group 3)* pushing toward blocked exits on the south wall. $k_D = 0$, $k_S = 7$, $\phi = 125$, time step 11.

haviours in the model by disregarding line 9 of STEP in algorithm 1.

Analysis and understanding of the results depends on a description of the behaviour of the model agents. Observations reveal that there are three categories of agents at the outset of the simulation:

1. agents unaware of the blocked exits (naïve agents with $\psi = 0$) located in the half of the room closest to the doors,

2. agents aware of the blocked exits (knowledgeable agents with $\psi = 1$) who are located within two cells of the blocked exits, and

3. naïve agents located in the half of the room closest to the blocked exits.

These categories, or groups, exhibit different behaviours and have different outcomes. The outcome for an agent is not solely affected by its group membership, as there is also an interaction with agent drive.

### 3.2.1 High drive and moderate drive cases

Observation of the simulation (see figure 7) reveals the behaviour interactions between the three groups of agents, which differ only in degree between the high and moderate drive cases. Because of the influence of the static field in these cases, the agents move rapidly toward the closest exit. Group 1 agents are free to move toward the true exits and exit readily, never becoming aware of the blocked exits. Group 2 agents (who are joined within the first few time-steps by a small number of group 3 agents close to the blocked exits) realise that they are at the wrong end of the room and begin to move toward the real exits. The remaining group 3 agents approach the blocked exits and encounter group 2 trying to move in the opposite direction.

In these cases, group 3 quickly forms a barrier for group 2 and vice versa. Because the exits are spaced evenly along the walls, the group 3 agents form into a band stretching from wall to wall; because of the large number of group 3 agents, the band is many agents deep, and (barring injuries) can physically push group 2 back toward the blocked exits. In the high drive case, the band forms rapidly, is high density and is impenetrable to group 2. In the moderate drive case, the band is slower to form, is less dense, and some group 2 agents are able to infiltrate themselves through the band. What is particularly interesting about this barrier formation is that the jam occurs in open space, and is not catalysed by physical structures such as bottlenecks, narrowings or obstacles.

Let us take up the question of injuries. Injuries (figure 8) followed the pattern of previous studies in that higher drive to achieve goals results in more injuries [6, 10]. As discussed in section 3.1, injury rates are generally lower than in these previous studies because there are ample exits available along one wall, which accommodate many agents per time step. The porous wall reduces crowd density and hence movement conflicts at the exit.

Observation reveals that remaining injuries are primarily concentrated where groups 2 and 3 meet. This is consistent with Fruin's observation that injuries within a crowd are not distributed at random, but follow patterns of force that accord with the context of the situation [27]. Injuries occur as group 2 agents (unable to make their way forward) exert force upon the tightly packed crowd of group 3 agents, and vice versa. As $\phi$ increases, injuries fall as the agents are not numerous enough to bring a crushing force to bear. (Recall that group 1 agents exit quickly in all cases, limiting the number of individuals and consequently the force applied.) Regardless of whether the situation is complicated by injuries or not, the stable barrier formation persists and a stalemate ensues in which neither group 2 nor group 3 exits the modelled area.

This stable configuration — with or without injuries — explains the fact that exit rates are independent of $\phi$ in this scenario, while injury rates are not. The pattern of exits engendered by the model (figure 9a), together with our observations, confirm that group 2 agents (with $\psi = 1$) are, for the most part, unable to exit in this scenario. In the high drive case only 1.3 knowledgeable agents on average manage to exit; they originate adjacent to the blocked exits and are able to move toward the real exits before the group 3 agents have fully blocked the route. In the moderate drive case the group 3 agents approach more slowly, giving on average 32.8 group 2 agents a chance to escape the barrier formation and move to the exit. The numbers of agents exiting with $\psi = 0$ in both the high and medium drive cases is the same because these are the group 1 agents (expected to number half of the 1116 initial agents) who have time for a complete exit in both the high and moderate drive cases.

In terms of distance travelled (figure 9b), exiting knowledgeable agents with $\psi = 1$ required many more steps to exit than did naïve agents with $\psi = 0$. Note that agents exiting with $\psi = 1$ may have originated either in group 2 (knowledgeable at the outset) or in group 3 (naïve at the outset, but gaining knowledge through discovery).

### 3.2.2 Low drive to exit

Model behaviour when drive to exit is low is quite different from the previous cases. In this case, the low influence of $k_S$ relative to $k_D$ means that agents display only a weak movement bias toward areas believed to be exits. The classification of agents into three groups is still meaningful in terms of explaining their behaviour, but the dramatic conflict between groups 2 and 3 does not occur. This is because the group 3 agents do not move toward the blocked exits in large numbers. They leave large spaces that allow group 2 agents the freedom to infiltrate through group 3 in moving toward the real exits. Indeed, the space created by moving group 2 agents allows agents from group 3 to move into the blocked exit area, discover the blockage, and join the

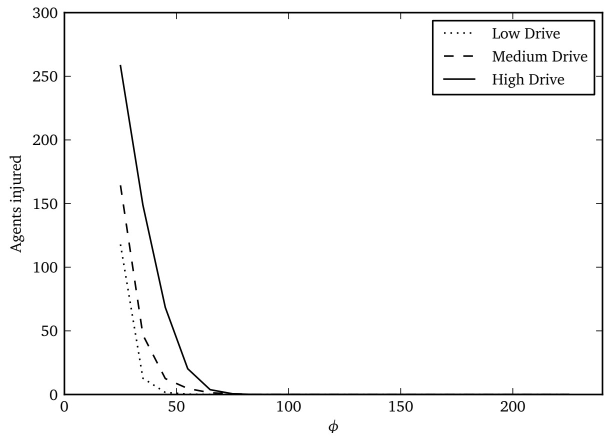
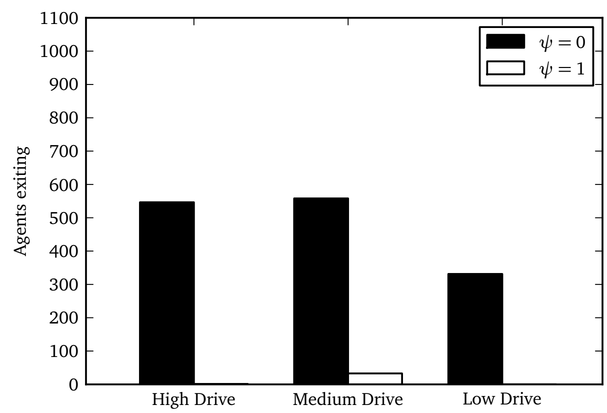
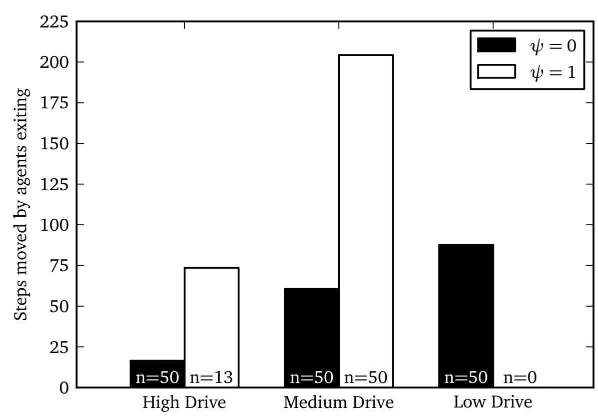



**Figure 8:** Heterogenous crowd: Agents injured.




**a.** number exiting. (Mean over 50 replications)




**b.** mean steps taken by agents exiting. (Note that this measure is undefined if no agent exits in a particular replication. Here we calculate the mean across the $\frac{n}{50}$ replications in which agents exited.)

**Figure 9:** Heterogenous crowd: Agent egress measures. ($\phi = 125$)

group 2 agents in moving toward the open exits.

Referring to figure 9, however, it is clear that avoidance of a stalemate between groups 2 and 3 does not translate into exits by knowledgeable agents with $\psi = 1$. This is because the agents, even though they are knowledgeable about blocked exits are simply not driven to move toward the real exits. The exit and step pattern for low drive agents in figure 9 is essentially the same as that shown in the baseline case of figure 5.

In summary, section 3.1 determined that a scenario having the same number of real exits as this one resulted in unimpeded egress and minimal injury. In the present scenario, simply by introducing belief in a set of blocked exits, the heterogeneity of the crowd resulted in jamming in open space, a much lower exit rate and a much higher injury rate. In this case the conflict occurred due to agents working at cross-purposes. Agents that had discovered information moved one way, while agents who had yet to discover the information moved in the other. The difference in behaviour and results between these two physically identical scenarios underscores the importance of modelling human behaviour in microscopic crowd models.

In this scenario, the communication potential of the agents was suppressed, and so physical discovery of information was required to change behaviour. Let us now determine the effects of inter-agent communication by activating the communication simulation within the model.

## 3.3 Heterogeneous crowd with communication

In this scenario we take up exactly the same situation as in section 3.2, except that we now enable the communication functionality of the model (line 9 of STEP in algorithm 1). In cases where they are blocked in movement, agents will now communicate their view selector to the blocking agent.

Observation reveals that in this scenario, the same three groups arise at the outset of the simulation as did in the last scenario. As the simulation unfolds, however, the barrier formation where naïve group 3 agents and knowledgeable group 2 agents jam one another in place does not occur. Here, a human factor (communication) has eliminated jamming forces by altering agent goals. When a naïve agent moves to block a knowledgeable one in this scenario, the knowledgeable agent communicates its view of the world, updating the $\psi$ value of the naïve one; this has the effect of explaining the blocked exit condition to the naïve agent, turning it into a knowledgeable one. Both agents move off toward the real exits, informing other conflicting agents on the way.

**Table 1:** Comparison of mean agent knowledge ($\overline{\psi}$) where $\phi = 125$.

| | drive | | |
|---|---|---|---|
| scenario | low | medium | high |
| §3.2 (no communication) | 0.253 | 0.407 | 0.113 |
| §3.3 (communication) | 0.817 | 0.649 | 0.553 |

### 3.3.1 Effectiveness of communication

With our numerical measure of agent knowledge ($\psi$), we can quantify the increased knowledge in the system that results from communication. Table 1 shows $\overline{\psi}$ across all agents (whether injured, exited or remaining) at each drive level at the conclusion of this scenario and that of section 3.2.

In the previous, non-communicating, scenario, average knowledge was generally low. This was particularly the case at high drive, when the barrier formation limited the number of agents who could discover the exits. Knowledge was also low at low drive, when few agents bothered to travel any distance, and so did not discover the blocked exits.

In the communicating scenario, by contrast, average knowledge is high. In this scenario knowledgeable agents are the rule; even exiting group 1 agents learn of the blocked exits. This is because of a wave of knowledgeable group 2 and 3 agents that quickly crosses the room. When the wave arrives at the sub-crowd of group 1 agents who are waiting to exit, the knowledgeable agents communicate with the rearmost agents in the sub-crowd. These rearmost agents, in turn, will communicate with those in front of them. As word travels quickly in a dense crowd, soon all agents exiting are knowledgeable. Those group 1 agents who exit before the arrival of the knowledgeable ones are essentially the only agents who never learn of the blocked exits. (This explains the drop in knowledge at higher drives, when more group 1 agents exit before the wave of group 2 and 3 agents arrives.)

### 3.3.2 Effect on injuries and exit rates

The injury and exit rates in this scenario demonstrate the potential benefits of successful communication. Injury rates for this scenario (figure 10) are much improved from the non-communicating case (figure 8), to the point of being comparable (if not identical) to the results of the homogeneous scenario (figure 4) in which all agents were knowledgeable.

Figure 11 shows exit results compared to the baseline case of section 3.1, and figure 12 shows the exit results and steps taken broken down by $\psi$. When agent drive

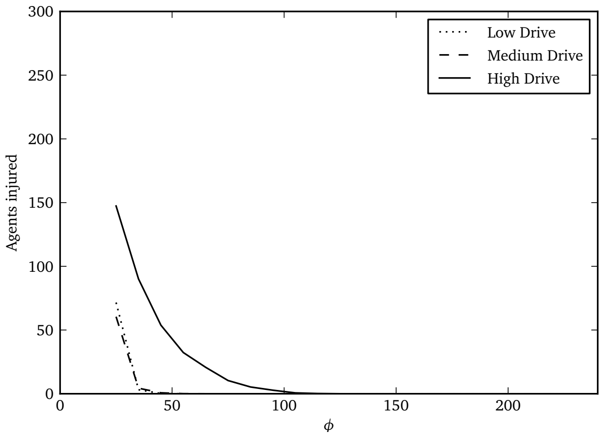



**Figure 10:** Heterogeneous crowd with communication: Agents injured.

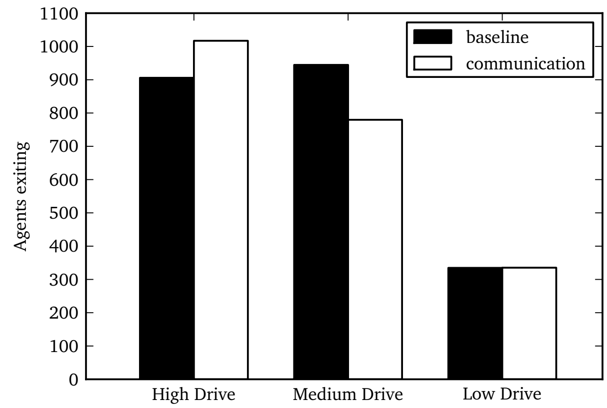
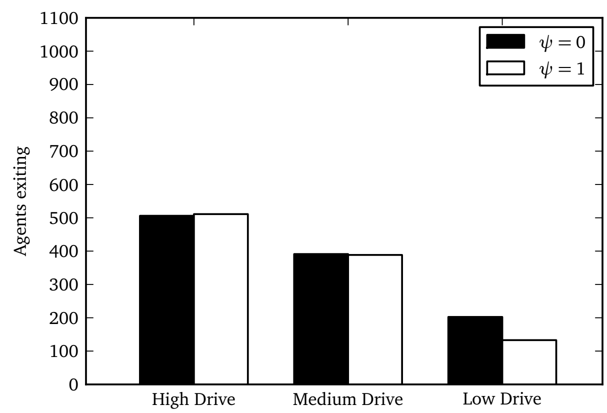



**Figure 11:** Number exiting in the 'heterogeneous crowd with communication' scenario (*communication*) compared to the 'homogeneous' scenario (*baseline*). (Section 3.1 vs. section 3.3.) $\phi = 125$

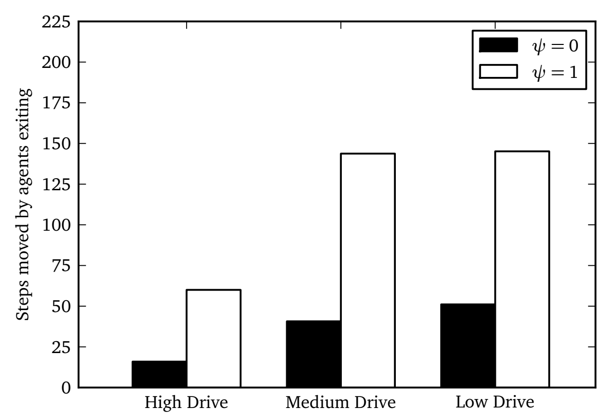
was high, total exits were actually improved slightly from the baseline case (as were injuries); this occurred due to the increased number of steps for group 3 in this scenario. The larger number of steps for agents in group 3 had the effect of delaying their arrival at the exits, consequently reducing density and pressure (and hence injuries and delays due to jamming) in that area.[3]

While more high drive agents exited compared to the homogeneous scenario, fewer moderate drive agents did. This was due to the larger distance covered by group 3 agents who initially moved away from the real exits; at moderate drive, the slower pace of these agents limited the number who could travel this additional distance and still exit within the limited time available. (This underscores the importance of timely and accurate information in evacuations.) At low drive, the same number of agents exited as in the baseline case (drive being the limiting factor on egress in this case rather than knowledge).

In interpreting the figure 12 breakdown by $\psi$ value, we must bear in mind the discussion of section 3.3.1: communication causes transitions in $\psi$ at exit time if there is a jam at exits. Many agents exiting from the jam are knowledgeable, even though this knowledge was incidental to their egress strategy. Similar challenges relating to determining who knew what and when also occur in investigations of real crowd incidents, and explain the focus of investigators on *when* people become aware of various aspects of a situation. This level of data collection is beyond the scope of what




**a.** number exiting.




**b.** steps taken by agents exiting.

**Figure 12:** Heterogenous crowd with communication: Agent egress measures. ($\phi = 125$)

[3]Although the purpose of the present article is not a microscopic investigation of high-density-jamming (c.f. [6, 10, 23, 30–32]), it is interesting that delayed arrival reduced the density sufficiently that high drive to exit resulted in the best exit performance. These results support the view that if density can be managed, a physical geometry can support faster speeds.

is reported here, leading to watering-down of differences between groups in figure 12.

This point is important in understanding the appearance of even exit rates between $\psi$ values in figure 12a. Unlike in section 3.2, some exiting group 1 agents exit with $\psi = 1$. Thus $\psi$ is a poor predictor of group membership in this scenario. Despite this, figure 12b shows that heterogeneity is preserved in the crowd. Even with some watering-down of differences between groups, agents with $\psi = 1$ still take approximately three times as many steps to exit on average. Thus, although communication helps conflicting agents to act in a more coordinated manner, figure 12b demonstrates continued heterogeneity (and thus non-interchangeability) when an agent's personal history is considered; the time-line of knowledge acquisition for each agent influences their pattern of movement over the life of the simulation — and, ultimately, their time to exit.

# 4 Discussion

## 4.1 Freezing by heating at Central Lenin Stadium

The present results can be related to a crowd disaster that occurred on October 20, 1982, when an international soccer match was played between Spartak Moscow and the Dutch HFC Haarlem at Central Lenin Stadium in Moscow. Although there are discrepancies in details between official and unofficial accounts, the disaster has come to be "acknowledged as the world's worst soccer tragedy" [33]. Fans began to exit the stadium down a dark icy hallway before the end of the game. When a late goal was scored, the sound of the cheering from within caused these fans to attempt re-entry. The re-entering fans met large numbers of exiting ones (a single section of the stadium contained 10 000 fans) in what has been described as a human mincer. Although numbers of dead were initially reported as "little more than a dozen", and eventually at 61 by Soviet authorities, an independent report seven years later put the number at 340, and this number is commonly used in references to the event for memorial purposes. [33–36]

The Lenin stadium disaster and the barrier formation described in section 3.2.1 are examples of counter-flow clogging that has been modelled in discrete systems [37] and later in continuous ones also [38]. Schmittmann et al. described a phase transition in which oppositely charged particles, driven to approach each other from opposite directions by an external field, become segregated into a stable structure due to mutual blocking. They found that high mass density (particle density regardless of charge) and drive favoured this transition [37], sometimes termed *freezing by heating*.

Although the work of Schmittmann and colleagues concerns stochastic lattice gases, it is relevant to understanding the barrier formations we observed and the clogging at Lenin stadium. In crowds, freezing by heating predicts that when drive is low, crowd tolerances (in a physical sense) may be higher than when drive is high. Consider two facing groups of pedestrians crossing the street. These two groups need to pass through one another in the crosswalk. Slow speeds promote smooth and efficient flow as people have time to find a space through the opposing crowd. If the groups attempt to cross at a run, however, there will be insufficient time to make this accommodation and there will be collisions and jamming in the crosswalk. High density compounds this effect — a few pedestrians may be able to avoid each other while crossing quickly, while large groups may need to move quite slowly to allow for free passage.

With sufficiently large crowds and high drive, the Lenin stadium example demonstrates how freezing by heating can lead to a crowd disaster; two crowds attempted to pass through one another with high drive brought on by the excitement of an international sports match. (It should be noted that the heterogeneity of the crowd goals was an important factor in this disaster. Thus, a model wishing to study this disaster requires the capability to represent a heterogeneous crowd.)

We note a strong correspondence by which the heterogeneous crowd, barrier formation, stasis and injuries in section 3.2 echo the disaster at Lenin Stadium; both are consistent with the freezing by heating effect in counter-flow. This correspondence reinforces the validity of our quantitative model results. Our results support the view that slower collective progress can result from higher individual drive in crowds with conflicting movement goals. When we introduced differing agent goals through discovery of information in section 3.2 we demonstrated the freezing by heating effect in the barrier formation created — in open space, independently of the physical geometry — by the interaction between groups 2 and 3:

- At low agent drive, crowd densities and speeds remain low, allowing for an accommodation as groups 2 and 3 infiltrate themselves through the gaps in the opposing group.
- When drive becomes moderate, the density increases and there are many fewer empty spaces in the band formed by group 3. This leads to interference between the groups and limited potential for group 2 agents to access the real exits.

- In the high drive case, the group 3 agents essentially form an impenetrable wall, and the group 2 agents are pinned behind it.

Thus, as particle drive within the system increases from low to high, the resultant pattern of interaction between the groups becomes more rigid, culminating in a frozen stand-off when drive is highest.

By introducing heterogeneity into a crowd movement model, we have been able to demonstrate a freezing by heating which is not seen if all agents behave identically in their move toward the exits. Although jams in counter-flow have been previously studied (in the floor field model [15], in other cellular automata and lattice gas models (e.g. [39–41]) and in continuous simulations [42]) scenarios have typically involved simple, orchestrated jams obtained by directing fixed groups of agents at one another with no involvement of force or 'heating.' In the case of the floor-field model studies [15] this approach was required as the model was not yet able to study force related effects (introduced in [10]) or the emergence of groups (introduced here through dynamic discovery of spatial information and communication). Thus the present improvements have enhanced our ability to study complex situations such as emergent jamming in counter-flows.

## 4.2 Information during emergency egress

It has been noted in the context of fire disasters that providing timely, specific, authoritative and accurate information improves safety by increasing available time to evacuate [8]. Our results suggest a second way that information can improve safety: a reduction in counterflow through common movement objectives. We have seen in section 3.3 that good information (as well as communication between crowd members) eliminated the barrier formation when agents recruited others to a mutually beneficial movement strategy. This resulted in an increased exit rate and decreased injuries.

Interestingly, these two observations can interact when information is low. When information is withheld, available safe escape time for occupants is reduced due to delay in pre-movement time [8]. The consequent smaller window for escape can increase drive to exit, which is associated with higher densities, lower exit rates and more injuries [6]. Independently, as our results suggest, absence of good information and communication can also lead to paradoxical effects like jamming in open space that further reduce crowd safety. The interaction occurs between these two problems: As available time decreases and drive increases, density rises and jamming is more likely to occur (through freezing by heating) and its effects are more severe. Jamming reduces exit efficiency, which further wastes the available safe escape time and increases the drive to exit in the remaining time, which contributes to further heating in the system.

Of course, an additional pre-requisite for smooth pedestrian flow is a physical geometry that supports movement without counter or crossing flows (c.f. [43]). Our results show the importance, however, of considering more than just physical factors. If accurate information is shared with evacuating building occupants in a timely manner then: available escape time can lengthen and drive can consequently decrease, movement patterns can become more felicitous and the risk of counter-flow clogging can be consequently reduced. These characteristics would ultimately suggest a safer evacuation.

## 4.3 Situatedness and knowledge representation

Let us now consider heterogeneity itself in the crowd context. In a sense, the original floor field model can be seen as supporting a heterogeneous crowd because the static field can break a crowd into sub-crowds that move toward differing targets at the outset of the simulation. This occurs because the floor field model naturally provides for a situated simulation. In keeping with the concept of situated cognition in cognitive science [44], agents directly consult their immediate surroundings (the local neighbourhood in the static field) regularly, making local movement decisions based on current conditions (including the movement of other local agents); this can be contrasted with a traditional artificial intelligence approach to planning that precomputes complete and optimal paths in an abstract planning environment, with the actual path traversal delegated to a separate system in a distinct process [45].

The heterogeneity present in our model goes beyond the sub-crowd-based heterogeneity of the floor field model. This is because the sub-crowds in the floor field model are themselves homogeneous. We have introduced a mechanism for agents to be part of the same crowd, in the same physical area, and yet not be focused on the same objectives.

The differences in exit performance by agents with different information states (represented within the model by different values of $\psi$) does quantify a pattern of heterogeneous behaviour within the crowd. We note, however, that differences *within* information states can be as important as differences *between* such states. For example, agents with $\psi = 0$ are divided into groups 1 and 3 because of situated information processing despite their identical mental content. This difference in behaviour between agents that have the same mental content demonstrates the tightness with which the human factors of information processing and communication have been integrated with the force-enabled floor field model; by integrating knowledge representation at the level of movement rules within the individual, our method produces agents that remain highly situated. This argues for the practicality of implementing human factors at the microscopic level, here accomplished using the microscopic human factors approach.

# 5 Conclusion

By extending the floor field model, we have created a microscopic model of information discovery, information processing, communication and representation of knowledge. Basing our specification on Sime's observation that crowd situations are information systems through which people move, we have allowed agents within the model to obtain spatial information from the environment during circulation and to act on this information, creating a dynamically heterogeneous crowd. Obtaining new information leads to new movement goals, and, depending on agent drive, conflicts between agents of varying severity. Through freezing by heating, these conflicts can lead to a barrier formation echoing the Central Lenin Stadium disaster, rooted not in physical geometry but rather in opposing crowd forces. We found that communication can have a powerful reducing influence on these forces when it causes agents in opposing groups to adopt mutually beneficial movement patterns. We found that communication eliminated the barrier formation in the simulation, resulting in dramatic increases in exits and decreases in injuries.

Although it may seem evident, it is worth noting that the ability to represent heterogeneity in crowds through discovery of information and changing mental content allows for modelling of more complex and realistic scenarios. Although we can fix mental content at the outset of a simulation, this allows for studying only simple scenarios in which agents are interchangeable and not particularly realistic. As we have seen in our blocked exit simulation, and as seen at Lenin stadium, many situations unfold in several phases; without being able to represent changing goals we are unable to represent these phases within the model. If a model cannot represent these non-trivial — but interesting — scenarios, it misses out on discovering the interesting interactions between groups in the simulation.

At the beginning of this article, we discussed the limitations of taking people to be homogeneous, interchangeable ball bearings. Our individuals are no longer interchangeable; their personal history within the simulation is now relevant to understanding their behaviour and performance. Thus, with the aid of the microscopic human factors methodology, we have improved the relevance of our modelled individuals to real people.

There is ample room for further work in this regard, as egress researchers have begun to consider the role of occupant experience with physical structures in understanding behaviour. The 'fire and ICE' concept [46], for example, argues that a consideration of learning by occupants — by exposure to information during ingress and circulation — is crucial to understanding what they do in emergency egress. This observation suggests that egress models must become more general, simulating occupants in everyday use of a space as well as in egress, and allocating to evacuating agents the knowledge acquired during the exploration/occupancy phase [47]. An abstract investigation of this approach could use the model described here as a starting point, an interesting possibility for future work. Future work could also include making the abstract model more concrete (e.g. in the case of fire egress, to consider interactions with physical parameters such as available safe escape time [48]), to expand it to other human behaviours (e.g. to consider pre-movement [49]), to examine interactions with heterogeneous movement rates [20,21] and to examine situations with different exit configurations.

Looking at our results more broadly, we showed striking differences in behaviour between (i) a typical ball-bearing-like homogeneous crowd, (ii) a heterogeneous crowd in which different beliefs underlie opposing movement goals, and (iii) a heterogeneous crowd that communicates to reduce conflict and increase safety. Despite the fact that all three scenarios were physically identical, outcomes were very different. From this observation, and to the extent that the movement and force patterns simulated are indicative of human responses to salient information, we draw two conclusions:

- First, as opposed to simple panic, the results underscore the importance of studying information, how it is processed and where and when it is obtained in understanding crowd dynamics and crowd disasters.

- Second, the striking differences between the scenarios, however rudimentary, illustrates both the potential and urgent necessity of incorporating human factors into microscopic crowd models.

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