

# 1 **Simulating Effects of Signage, Groups and Crowds on Emergent Evacuation Patterns**

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4

## 5 **Abstract**

6 Studies of past emergency events have revealed that occupants' behaviors, egress signage system, local  
7 geometry, and environmental constraints affect crowd movement and govern the building evacuation. In  
8 addition to complying with code and standards, building designers need to consider the occupants' social  
9 characteristics and the unique layout of the buildings to design occupant-centric egress systems. This paper  
10 describes an agent-based egress simulation tool, SAFEgress, which incorporates important human and  
11 social behaviors observed by researchers in safety and disaster management. Agents in SAFEgress are  
12 capable of perceiving building emergency features in the virtual environment and deciding their behaviors  
13 and navigation. In particular, we describe four agent behavioral models, namely, following familiar exits,  
14 following cues from building features, navigating with social groups, and following crowds. We use  
15 SAFEgress to study how agents (mimicking building occupants) react to different signage arrangements in  
16 a modeled environment. We explore agents' reactions to cues as an emergent phenomenon, shaped by the  
17 interactions among groups and crowds. Simulation results from the prototype reveal that different designs  
18 of building emergency features and levels of group interactions can trigger different crowd flow patterns  
19 and affect overall egress performance. By considering the occupants' perception about the emergency  
20 features using the SAFEgress prototype, engineers, designers, and facility managers can study the human

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21 factors that may influence an egress situation and, thereby, improve the design of safe egress systems and  
22 procedures.

23 **Keywords:** crowd simulation, egress simulation, building egress, social agents, social behavior, collective  
24 behavior, simulated perception

25

## 26 **1. Introduction**

27 We designed a computer model (Social Agent for Egress or SAFEgress) for studying how agents react  
28 to cues in emergency situations. Instead of treating agents as isolated atoms reacting to emergency  
29 scenarios, we embedded them into social groups, each defined by a unique social structure and group norm.  
30 The agents make decisions considering group members and neighbors, in addition to individual preferences.  
31 Moreover, each agent is equipped with the capabilities of sensing, reasoning, memorizing, and locomotion  
32 to decide and execute its actions. This setting allows us to explore reactions to cues as an emergent  
33 phenomenon, shaped by the interactions between individual preferences, group characteristics and crowd  
34 behaviors.

35 Specifically, we use SAFEgress to study the impacts of different exit signage systems within the  
36 constraints of a given building layout. Simulation results from our demonstration indicate that occupants'  
37 exit preferences, visual perception of the signage system, herding behavior, and social behavior among  
38 groups can lead to very different reactions to cues. The results can be used to suggest potential  
39 improvements in the placement of exit signs in order to trigger more efficient evacuations from buildings  
40 during emergencies. Furthermore, our model also has applications outside the field of induced behavioral  
41 change. For instance, SAFEgress can be used to study the effects of human and social behaviors on  
42 collective crowd movement patterns. Most egress simulation tools assume simplistic behavioral rules and  
43 mostly ignore social behaviors of the agents (Aguirre et al., 2011; Kuligowski 2011). By modeling agents  
44 with social behaviors, SAFEgress addresses these deficiencies.

45 This paper is organized as follows: Section 2 describes the related work in modeling human and social  
46 behaviors in egress. Section 3 explains the SAFEgress simulation platform and the key components of the  
47 platform. Section 4 describes some examples of plausible egress behaviors in the current prototype. Section  
48 5 concludes the paper with discussion.

## 49 **2. Related work**

### 50 **2.1. Social behaviors during emergencies**

51 A *shikake* is a mechanism or a device that triggers a behavioral change. Matsumura (2013) defines a  
52 shikake more precisely using three interrelated factors: (1) a shikake is an embodied trigger for behavioral  
53 change; (2) the trigger is designed to induce a specific behavior; and (3) the behavior solves a personal or  
54 social issue. These factors highlight that a shikake is a practical and simple mechanism that offers a solution  
55 to a (social or personal) problem (Matsumura 2013). For example, the placing of fly targets in urinals in  
56 airports reduced spillage by 80% due to the propensity of men to aim at the fly. In turn, reduced spillage  
57 contributed toward reducing cleaning time and water consumption (Matsumura and Fruchter 2013). The  
58 simplicity of a shikake rests on the complexity of the psychological or social mechanism it triggers  
59 (Rosenberg et al. 2013; Salganick et. al., 2006). In this paper we focus more on the latter, keeping  
60 psychological processes in the background. Before describing how we model the social behavior of agents,  
61 we review the previous literature on how people react to emergency scenarios.

62 Post-fire studies have shown that occupants in emergencies do not act randomly, as if in a panic, nor act  
63 in an identical manner without individual cognitive ability as if they are physical molecules (Aguirre, 1998;  
64 Drury et al., 2009; Sime, 1983; McPhail, 1991). Rather, occupants in emergencies often base their actions  
65 on their past experience, social structures, and perceptions and interactions with others to define an  
66 emergent understanding of the situation. For example, the affiliative theory (Mawson, 2005; Sime, 1983)  
67 and place script theory (Tong and Canter, 1985) examine individuals' behaviors based on their personal  
68 knowledge, risk perceptions, experience, and routines. The emergent norm theory (ENT) specifies that

69 disasters may lead to collective behavior through the process of milling and keynoting (Turner and Killian  
70 1987). Milling is a communication process whereby individuals in a collective attempt to define the  
71 situation, while during keynoting, leaders emerge, interpret the situation and make suggestions on what to  
72 do next (McPhail, 1991). Aguirre (1998) further applied ENT to explain occupants' reactions in the World  
73 Trade Center Explosion in 1993, and showed that social groups and enduring social relationships could  
74 lengthen the time of evacuation.

75 ENT and the pro social theory suggest that people continue to maintain group structure and behave in a  
76 pro social manner during emergencies (Aguirre et al., 2011). The social identity theory infers that people  
77 have a tendency to categorize themselves into one or more "in-groups," building their identity in part on  
78 their membership in the groups and enforcing boundaries with other groups (Drury et al., 2009). Moreover,  
79 studies in sociology and psychology suggest that people influence each other's behaviors through the  
80 spreading of information and emotions (Rydgren, 2009; Hoogendoorn et al., 2010).

81 Researchers in safety and disaster management have proposed theoretical frameworks that describe the  
82 processes of seeking information, interpreting the situation, assessing the risk, and making decisions  
83 specifically in response to a disaster. For example, Lindell and Perry (2011) applied the Protective Action  
84 Decision Model (PADM) to examine the disaster response of occupants in residential fires and study the  
85 effect of warning mechanisms on evacuation time. Based on the PADM framework, Kuligowski (2011)  
86 studied the actions taken during the pre-evacuation period of the 911 WTC (World Trade Centers) attacks  
87 and developed a model to qualitatively describe how occupants made their decisions to evacuate. Reneke  
88 (2013) proposed the Evacuation Decision Model to predict the state of the occupants by modeling the level  
89 of risk perception and the effect of knowledge, social influence, and alarm as they occur over time during  
90 the pre-evacuation period. These frameworks and models synthesize human behaviors in emergencies as  
91 process models that can be systematically analyzed further by incorporating factors, such as threats, social  
92 relationships, and personal experience, to determine the outcome of evacuation.

93 In light of prior studies, we conjecture that creating a shikake for egress will require individual, group,  
94 and crowd-level characteristics. At the individual level, occupants may refer to their past experiences and  
95 knowledge and their perceptions of the situation to decide on their actions. At the group level, the pre-  
96 existing social structure (relations between group members) and group norms (expectations of each other's  
97 behavior) affect the behavior of an individual. Crowd-level behaviors are emergent phenomena and often  
98 follow social norms.

99

## 100 **2.2. Current crowd simulation approaches**

101 Different crowd modeling approaches, such as the particle (Helbing et al., 2000; Moussaïd et al., 2011),  
102 cellular automata (Burstedde et al., 2001), and agent-based systems (Lin et al., 2010; Galea et al., 1998;  
103 Durupinar et al., 2011; Musse and Thalmann, 2001; Aguirre et al., 2011), have been adopted into various  
104 simulation software to model crowd movement in virtual environments. Zheng, Zhong, and Liu (2007)  
105 have provided detailed reviews of the different simulation models. The following discussion focuses on the  
106 agent-based approach which is adopted in the implementation of SAFEgress.

107 Agent-based systems model the crowd as a collection of autonomous entities known as “agents” to  
108 represent the human occupants. These systems allow emergent phenomena as a result of interactions among  
109 the virtual agents. Many egress models have recently adopted this approach and proposed different  
110 representations of the spatial environment and the agents. One common way of representing the spatial  
111 environment is dividing the space into a 2-D array of cells where each cell contains up to a certain number  
112 of agents (Lin et al., 2010; Galea et al., 1998). While the grid-based spatial representation benefits from its  
113 computational efficiency, the representation limits agents’ spatial movements and can potentially show an  
114 unnatural checkerboard pattern when crowd density is high. Another approach is to represent the spatial  
115 environment as a continuous space that allows agents to navigate naturally on a continuous plane while  
116 considering constraints imposed by the physical geometry of the building (Durupinar et al., 2011; Musse

117 and Thalmann, 2001). Our simulation framework uses the continuous spatial representation which allows  
118 a wider array of locomotions of the agents as well as the simulation of high-density crowd scenarios, such  
119 as over-crowding and pushing at exit (Aguirre et al., 2011).

120 In most agent-based systems, the agent navigation routes are usually pre-defined by specifying explicitly  
121 the origins and destinations of the occupants (Aguirre et al., 2011; Turner and Penn, 2002). Optimal routes  
122 (usually defined in terms of travel time or distance) are obtained by assuming that the agents have good,  
123 often perfect, knowledge of the environment. Examples are the way-finding model in EXODUS  
124 (Veeraswamy et al., 2009) and the simulation model proposed by Kneidl et al. (2013). Other agent-based  
125 systems model an agent's navigation decision as the outcome of decision-making processes, rather than  
126 pre-defined or optimized routes. For example, ViCrowd (Musse and Thalmann, 2001) is a crowd simulation  
127 tool in which crowd behaviors are modeled as scripted behaviors, as a set of dynamic behavioral rules using  
128 events and reactions, or as externally controlled behaviors in real time. MASSEgress (Pan, 2006) gauges  
129 an agent's urgency level, evaluate behavior models represented as decision trees, and invokes a particular  
130 behavior to determine the navigation target. These models consider agents' behaviors as a perceptive and  
131 dynamic process subjected to external changes. We also adopt the perceptive approach in SAFEgress when  
132 updating the agents' behaviors.

133 As noted by Kuligowski and Peacock (2005), a wide variety of computational tools for egress simulation  
134 are available; however, human and crowd behaviors are often ignored and group effects on evacuation  
135 patterns are seldom explored (Challenger et al., 2009; Aguirre et al., 2011). Only recently have efforts been  
136 attempted to incorporate social behaviors into egress simulations. For example, Tsai et al. (2011)  
137 implemented exit knowledge, families, and emotional contagion on evacuation and evaluated the impacts  
138 of emotional and informational interactions between agents. Similarly, Aguirre et al. (2011) described an  
139 agent-based model which attempts to implement the pro social model in simulating emergency evacuations.  
140 Features, such as leaders and followers within a group, have been implemented to simulate population at a  
141 group level and observe emergent patterns as a result of social relationships. Our model extends the notion

142 of pre-existing social relationships by defining groups with several salient attributes, such as intimacy level  
143 and group influence. Furthermore, we incorporate the effect of neighboring crowds on individuals and  
144 investigate crowd behaviors, such as herding, on the evacuation patterns.

145

### 146 **2.3. Model of spatial representation in simulations**

147 People's knowledge and memory of a space has a significant effect on their route choices. For example,  
148 when the desirable destinations (such as the entrance of the building) are not immediately visible, people  
149 refer to external information (such as signage) or memory of a specific route (such as following the paths  
150 which they traveled before) to determine their travel directions (Gärling et al. 1986). Moreover, researchers  
151 in environmental and cognitive psychology have argued that evacuees use their perceptions to guide their  
152 navigation (Gärling et al. 1986; Turner and Penn 2002). With proper spatial representation of the  
153 environment, Turner and Penn (2002) have shown that natural human movement can be reproduced in  
154 simulations without the needs to assign the agents with extra information about the location of destination  
155 and escape route.

156 To simulate the spatial cognitive capability of the agents, a proper representation of the spatial  
157 connectivity that can be used for navigation by the agents is needed (Turner and Penn 2002). The spatial  
158 connectivity is often represented as a navigation graph or a roadmap. A variety of techniques have been  
159 proposed to create a navigation graph from a given building geometry. Most of these techniques have been  
160 developed in the field of robotics (Latombe, 1995). Many space discretization techniques (such as Voronoi  
161 diagrams) have been used to derive a navigation graph. Although these techniques are commonly used for  
162 steering robots, they need to be modified for egress simulation for which human-like cognition and  
163 navigation are important. Approaches that are capable of more accurately modeling human perception and  
164 cognition are based on visibility graphs (Choset, 2005). A visibility graph consists of nodes defined by the  
165 physical geometry of the building, its special features and the destinations of the agents. An edge is added

166 to link two nodes if they are in the line of sight. In our work, we adopt a visibility graph to represent the  
167 spatial connectivity of a floor (Chu et al. 2014). The visibility graph is used in SAFEgress primarily as a  
168 representation of the continuous space to allow the agents to perceive possible areas to explore, rather than  
169 as a navigation guide that dictates the movement by the agents.

170

### 171 3. A simulation framework for modeling human and social behaviors

172 SAFEgress is an agent-based model designed to simulate human and social behaviors as well as  
173 emerging crowd behaviors during evacuations. In the following sections, we first provide an overview of  
174 SAFEgress framework and describe each major module of the system. We then briefly discuss the spatial  
175 representation, followed by the agent representation and the attributes used to model occupants in an  
176 emergency situation. Details of the system and the individual components have been described elsewhere  
177 (Chu et al. 2014; Chu and Law 2013).

#### 178 3.1. System architecture

179 SAFEgress is an agent-based model designed to simulate human and social behaviors as well as  
180 emerging crowd behaviors during evacuations. Figure 1 depicts the system architecture of SAFEgress. The  
181 key modules of the framework are the Global Database, Crowd Simulation Engine, and Agent Model, while  
182 the supporting sub-modules include the Situation Data Input Engine, Geometric Engine, Event Recorder,  
183 Population Generator, and Visualizer.

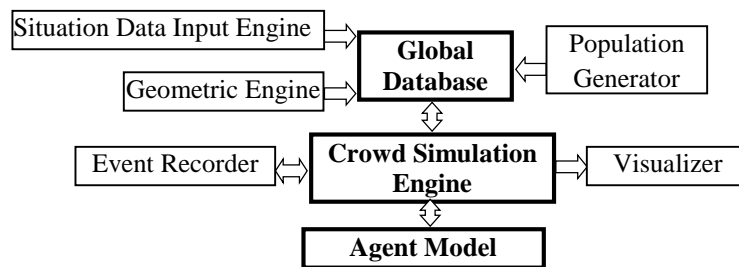


Figure 1. System architecture of SAFEgress (Chu and Law, 2013)

184



- 185 • The Global Database stores all the information about the agent population, the physical geometries,  
186 and the status of emergency situations. It maintains the state information (such as mental states,  
187 behavioral decisions, locations) of the agents.
- 188 • The Crowd Simulation Engine is the key module of the system. It interacts closely with the Agent  
189 Behavior Models Database, keeps track of the simulation, and records and retrieves information  
190 from the Global Database. The generated simulation results are sent to the Event Recorder and the  
191 Visualizer.
- 192 • The Agent Behavior Models Database contains the individual, group, and crowd behavioral  
193 models. Besides the default behavioral models, new models can be created by users to investigate  
194 a range of behaviors under different scenarios.
- 195 • The Situation Data Input Engine contains the properties of emergency cues and threats, such as fire  
196 alarms, smoke, and fire, which the virtual agents perceive during the simulation.
- 197 • The Geometric Engine maintains the spatial information, such as the physical geometry, exit signs,  
198 and openings about a facility. A virtual 3D model is built based on the spatial information and is  
199 used for collision avoidance and agent perception, as well as for visualization of simulation results.
- 200 • The Event Recorder stores the simulation results at each time step. The results can be retrieved for  
201 further analysis, such as identifying congestion areas and exit usages. The events captured can also  
202 be used to compare with known and archived scenarios.
- 203 • The Population Generator receives input assumptions of the agent population and generates the  
204 agents using physical (such as age, mobility, physical size) and behavioral profiles. This module  
205 can also generate both pre-defined and random social groups to study different social behaviors.
- 206 • The Visualizer, currently implemented using OpenGL, receives the positions of agents, overlays  
207 with the virtual 3D model, and then dynamically generates and displays simulation results as 2D/3D  
208 visual images.

209 The modular simulation framework allows investigation of crowd dynamics and incorporation of different  
210 behavioral models. Diverse populations of individuals and groups can be modeled and emergent collective  
211 behaviors can be simulated. In particular, efficient computational algorithms (such as detecting proximity  
212 and spatial visibility) have been carefully designed to allow simulations with a large number of agents.

### 213 3.2. Hierarchical space representation

214 Local building geometry, spatial arrangement of safety signage, and occupants' previous experience and  
215 familiarity with the buildings can significantly influence the choice of egress routes in emergencies. We  
216 design a space model to represent the virtual environment such that the agents can perform the following  
217 tasks:

- 218 • move naturally by avoiding collision with physical obstacles and walls;
- 219 • detect visible building features such as exit signs and door openings;
- 220 • support cognitive abilities of the agents, such as reasoning and acquiring knowledge of the  
221 building layouts.

222

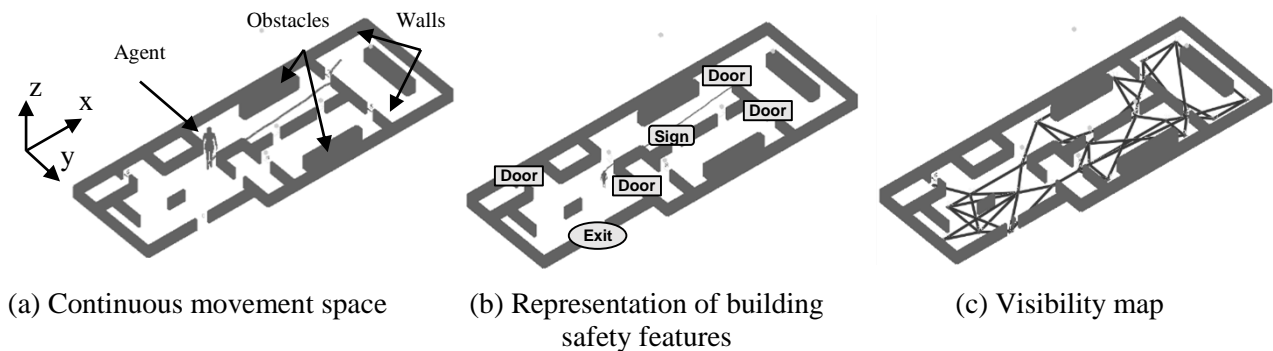


Figure 2. Three components of the hierarchical space model

223

224 As shown in Figure 2, the proposed hierarchical space model consists of three layered components: a  
225 continuous movement space, sematic representation of the building features, and a visibility graph. Each

226 component of the hierarchical space model is discussed further in the following sections. For computational  
227 efficiency, the space model is built prior to simulation and, once constructed, is used throughout the  
228 simulation, unless changes are made to the building layout that necessitate an update to the space model.

229

### 230 **3.2.1. Continuous movement space**

231 SAFEgress represents the spatial environment as a continuous space (as shown in Figure 2a) that the  
232 agents navigate. A typical floor space includes physical obstacles, such as walls and furniture. Agents  
233 navigate the virtual space and avoid colliding with physical obstacles. Using the user inputted building  
234 geometry, which describes the locations and the dimensions of the physical objects, such as walls and doors,  
235 the obstacle model is built to enable the agents to “sense” the physical surrounding and the visible space.  
236 To construct the obstacle model, the boundary surfaces of each 3-dimensional physical obstacle are  
237 represented as a set of polygon planes. Using the obstacle model, an agent performs two basic tests: (1)  
238 collision tests to determine its separating distances from nearby obstacles, and (2) visibility tests to  
239 determine if any given point in the virtual space is visible to the agent.

### 240 **3.2.2. Sematic representation of building safety features**

241 In an emergency situation, people observe relevant building features such as exits and exit signs to guide  
242 them to safety. These safety features provide additional information to the agents, such as the possible  
243 directions of travel leading to exit or outlet options. As illustrated in Figure 2b, three safety features (namely  
244 exits, exit signs, and doors) are included in the space model.

- 245 • Exit: The exit objects represent the outlets of the floor. The agents are equipped to visibly detect  
246 the exit objects. If an agent decides to escape through a particular exit object, the agent navigates  
247 towards the location of the exit object. Once reaching the exit, the agent is considered as  
248 physically exited from the floor space. The attributes describing an exit object are its spatial  
249 location and angle of orientation.

- 250           • Exit Sign: The exit sign objects represent the exit signs installed in a building as part of the  
251           egress system. The signs can be either directional or non-directional. Non-directional signs are  
252           attraction points for agents to move close to. A directional exit sign includes additional  
253           navigation direction. As an agent detects and decides to follow an exit sign, the agent extracts  
254           and follows the directional information as posted on the sign. The attributes describing the exit  
255           sign object include its spatial location, angle of orientation and, optionally, the directional  
256           information (such as left or right).
- 257           • Door: The door objects are similar to exit objects which serve as “attraction points” to the agents.  
258           Unlike an exit object which discharges the agent upon arrival, the agent remains in the floor  
259           space and continues to navigate until reaching an exit object. The attributes describing a door  
260           object are its spatial location and angle of orientation.

261   Although the selected building safety features (namely, exit, exit sign, and door) do not represent all the  
262   possible features that are found in a building, they are the most salient features pertaining to egress design  
263   and have great influence on people’s evacuation decisions.

264

### 265   **3.2.3. Visibility graph**

266   Navigation during an evacuation is motivated by the subsequent movements towards closer to the final  
267   destination (Gärling et al., 1986; Turner and Penn, 2002). Even with no apparent visual cues in the  
268   surroundings, humans move naturally in a direction that allows them to move further. To emulate natural  
269   human movement, we represent an obstacle-free space by populating the space with navigational points.  
270   Furthermore, we construct a visibility map to link the navigational points to represent the connectivity in  
271   the obstacle-free space. As shown in Figure 3, the visibility map is constructed using the following  
272   procedure:

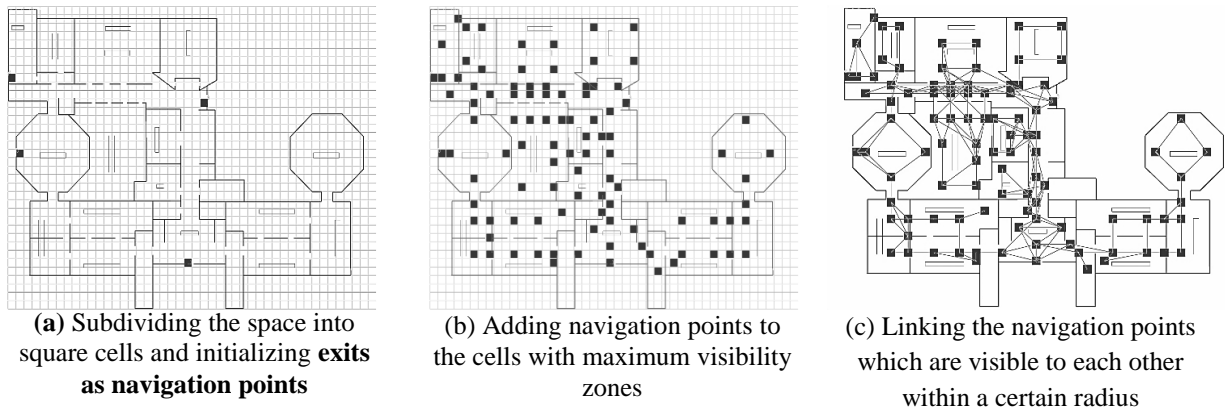


Figure 3. A procedure for generating visibility map (Chu et al. 2014)

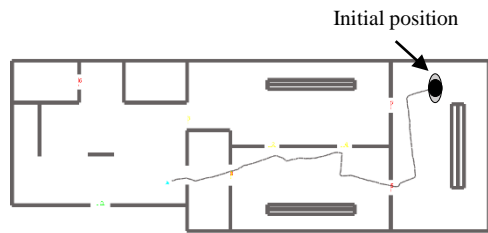
273 (1) The continuous space is first discretized into square cells to form a 2-D grid for computational  
 274 efficiency. The cells with the building features (such as exits, doors, and windows) are identified as an  
 275 initial set of navigation points (Figure 3a).

276 (2) For each cell on the 2-D grid, we compute the area that is visible from an agent in that cell (visibility  
 277 area). The cells that has the largest visibility area among its neighboring cells are identified and become  
 278 navigation points. Figure 3b illustrates the navigation points constructed for a floor space.

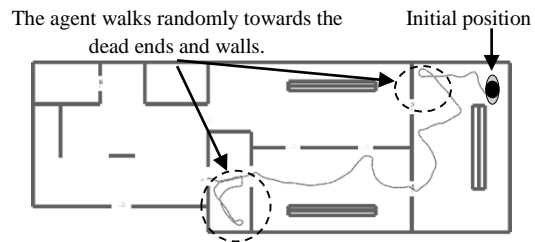
279 (3) Edges are added to link the navigation points that are visible to each other within a certain radius. The  
 280 resulting visibility map is a graph that represents the connectivity of traversal areas in the obstacle-free  
 281 space (Figure 3c). Specifically, Figure 3c shows the graph in which the nodes are the locations of the  
 282 building safety features and the intermediate navigation points, and the edges are pairs of nodes that  
 283 are visible from their locations.

284

285 The full visibility map represents the spatial connectivity of the floor which is customized based on the  
 286 building geometry and locations of the safety features. By querying the visibility map with its current  
 287 location, an agent “perceives” the possible navigation directions in the virtual space and makes subsequent  
 288 navigation decisions. Three basic rules are observed to define the use of the visibility map by the agents:



(a) Agent's trajectories with visibility graph



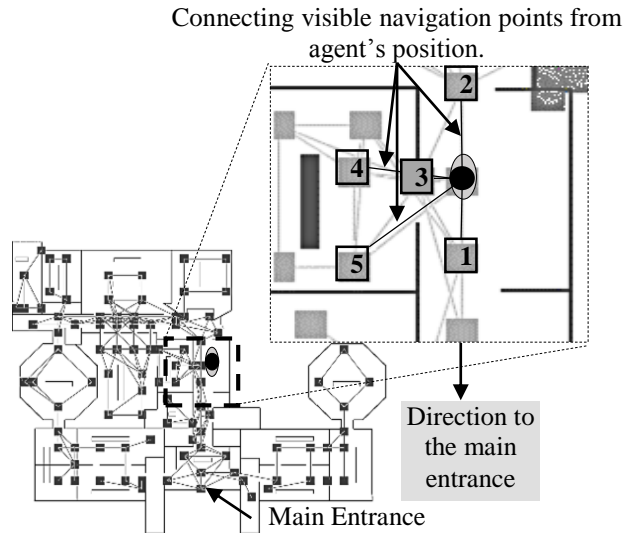
(b) Agent's trajectories without visibility graph  
(relying on collision avoidance)

Figure 4. Agent's trajectories navigating space with and without visibility graph

289

290 **Rule #1:** *An agent can detect the navigational points that are within the line of sight at each simulation*  
 291 *step.*

292 As humans can only perceive their local obstacle-free surroundings, the virtual agents can access only  
 293 the “visible” portion of the visibility map to decide their navigation directions. An agent queries the  
 294 visibility map with its current navigation point (determined based on its current location) to identify any  
 295 connecting navigation points that are visible to the agent. Figure 4 illustrates the differences of the agent's  
 296 trajectories with and without the visibility graph. With the notion of the visibility map as shown in Figure  
 297 4b, instead of relying on local collision avoidance with obstacles which can cause unnatural trajectories  
 298 (such as walking towards walls or blockages), the agent navigates the environment by detecting visible  
 299 navigational points and moving with reference to the next navigation points.



**Figure 5.** Illustration of visible navigation points from an agent (Chu et al. 2014)

300

301 **Rule #2:** *An agent chooses intermediate navigation points based on its navigation destinations and its*  
 302 *knowledge of the building.*

303 When an agent does not have a particular navigation destination, it chooses randomly one of the  
 304 navigation points to explore the space. When the agent has a particular navigation destination, it selects the  
 305 next navigation target based on its knowledge of the building layout. For example, an agent having the  
 306 knowledge of a familiar exit would choose among the navigation points the one that is nearest to the familiar  
 307 exit (Gärling et al., 1986; Turner and Penn, 2002). As illustrated in Figure 5, the agent, with knowledge of  
 308 the main entrance as its familiar exit, can weigh heavily and choose among the five visible navigation points  
 309 the navigation point labeled 1 to move closer to the main entrance. On the other hand, if an agent does not  
 310 have prior knowledge of the spatial layout, unless being influenced by other information, the agent assigns  
 311 equal weight to all the options and choose a navigation target randomly.

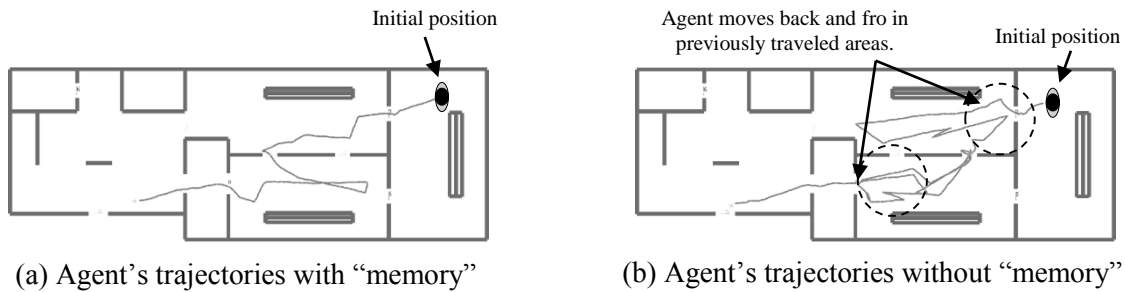


Figure 6. Agent's trajectories navigating space with and without memory

312

313 **Rule #3:** An agent "memorizes" the traveled space to avoid backtracking.

314 During the simulation, an agent can memorize the areas traveled by registering the traveled navigation  
 315 points in its cognition module. Less weight will be assigned to the visible navigation points that it has  
 316 traveled before. By doing so, the agent may avoid repeatedly visiting the same area. This cognitive ability  
 317 to memorize the previously traveled areas is particularly important for generating a natural navigation  
 318 trajectory in a situation that an agent has no prior knowledge of the environment and attempts to explore  
 319 the surroundings for exit. Figure 6 illustrates the differences in the trajectories by an agent with and without  
 320 memory. As shown in Figure 6a, the agent with memory tends to explore new areas with little backtracking.  
 321 In contrast, as depicted in Figure 6b, the agent without memory moves repeatedly back-and-forth to the  
 322 same areas.

323 With the notion of visibility map, the agents in SAFEgress can perceive the surrounding to: (1) identify  
 324 the obstacle-free space as visible navigation points; (2) transverse through the visible navigation points and  
 325 travel to a particular destination, such as the entrance used to enter the building, through intermediate  
 326 navigation points which are visible to the agents; and (3) construct a working memory of the spaces that  
 327 have traveled.

328



### 329 3.3. Agent representation of occupants

330 In SAFEgress, each individual is modeled as an autonomous agent who interacts with the dynamic  
331 environment and with other agents. Each agent is given a set of static and dynamic attributes to mimic the  
332 occupants. The choice of the attributes is crucial since they implicitly determine the range of simulation  
333 tests users can perform with SAFEgress. We select the attributes that are deemed important as reported by  
334 other researchers.

#### 335 3.3.1. Static attributes

336 Static attributes are defined prior to the simulation to specify their population type, experience profile,  
337 social group affiliation, and social traits. The agents' attributes, listed in Table 1, can be further categorized  
338 into three levels—individual, group, and crowd as described below (with the static attributes shown **in**  
339 **bold**):

- 340 • At the individual level, an agent has a **physical profile**, a **level of familiarity** (Mawson, 2005) with the  
341 building, and prior **known exits** (Sime, 1983) of at least one that the agent enters. The physical profile  
342 includes attributes such as age, gender, body size, travel speed, and personal space.
- 343 • At the group level, the attributes defined for social groups include a **group leader** (if any), the **group**  
344 **intimacy level** (e.g., high intimacy for a family group), the **group-seeking property** (describing  
345 agents' willingness to search for missing members), and the **group influence** (describing the influence  
346 of a member to the others in the same group) (Aguirre et al., 2011; McPhail, 1991). The agents  
347 belonging to the same group share the same group attributes.
- 348 • At the crowd level, an agent's social position is defined by the **social order** which reflects the likelihood  
349 of the agent to exhibit deference behavior (Drury et al., 2009). The lower the social order, the higher  
350 the chance for the agent to defer decision to other agents when negotiating the next move. A special  
351 agent, such as authority figures, a safety personnel, etc., may have **assigned roles**, and is responsible  
352 for executing actions, such as sharing information and giving instructions (Kuligowski, 2011).

353

**Table 1. Agents’ static attributes at the individual, group, and crowd level**

Individual	Group	Crowd
<ul style="list-style-type: none"> <li>• Physical profile               <ul style="list-style-type: none"> <li>○ Age</li> <li>○ Gender</li> <li>○ Body size</li> <li>○ travel speed</li> <li>○ personal space</li> </ul> </li> <li>• Familiarity</li> <li>• Known exits</li> </ul>	<ul style="list-style-type: none"> <li>• Group intimacy level</li> <li>• Group seeking</li> <li>• Group leader(s)</li> <li>• Group influence</li> </ul>	<ul style="list-style-type: none"> <li>• Social order</li> <li>• Assigned roles</li> </ul>

354

355 **3.3.2. Process model and dynamic attributes**

356 Based on the studies by researchers in disaster management and fire engineering about occupants’  
 357 behaviors during emergency (Lindell and Perry, 2011; Kuligowski, 2011), we implement a five-stage  
 358 process model (perception – interpretation – decision-making – execution – memorization) to update the  
 359 agents’ behaviors. Each stage in the process model is implemented as an independent computational  
 360 module. Table 2 summarizes the dynamic attributes which describe the perceived information and the  
 361 states of an agent at each stage. During the simulation, the dynamic attribute values are updated at each  
 362 process stage as described below (with dynamic attributes shown **in bold**):

- 363 • The Perception Module updates four attributes:
  - 364 ○ **Emergency cues**, such as smoke and alarm, that are visible or audible to the agent
  - 365 ○ **Visible floor objects**, such as doors and signs, that are visible to the agent
  - 366 ○ **Visible group members** that are visible to the agent
  - 367 ○ **Neighboring agents** that are visible to and are located within a certain radius from the agent
- 368 • The Interpretation Module maps the current knowledge of the agent into a set of internal thresholds  
 369 which describe the **urge** and **well-being** of the agent.

- 370 • The Decision-making Module invokes the decision tree modeling the behavior assigned to the agent.
- 371 Given the agent’s characteristics and the invoked decision tree, it looks up the agent’s **behavior** and
- 372 determines the long-term **navigation goal**, such as the familiar exit of the agent or the location of the
- 373 group leader, and the intermediate **navigation point** given the agent’s knowledge and location.
- 374 • The Locomotion Module calculates the agent’s movement toward the navigation target and returns the
- 375 updated **spatial position** of the agents, which are Cartesian coordinates (x, y, z) in the continuous space.
- 376 • The Memory Module registers the decision made during the simulation cycle and updates the **spatial**
- 377 **knowledge**. The **spatial knowledge** is an array storing the navigation points that the agents have
- 378 visited. The agents remembered the traveled navigation points and can later refer to the **spatial**
- 379 **knowledge** to avoid backtracking.

380 Each stage mimics a cognitive process or an act by an occupant during evacuation. Collectively, these  
 381 stages define the behavioral process of the occupants.

382 **Table 2. Agents’ dynamic attributes updated at different stages**

Perception	Interpretation	Decision-making	Locomotion	Memory
<ul style="list-style-type: none"> <li>• Emergency cues</li> <li>• Visible floor objects</li> <li>• Visible group Member</li> <li>• Neighboring agents</li> </ul>	<ul style="list-style-type: none"> <li>• Urge</li> <li>• Well-being</li> </ul>	<ul style="list-style-type: none"> <li>• Behavior</li> <li>• Navigation goal</li> <li>• Navigation point</li> </ul>	<ul style="list-style-type: none"> <li>• Spatial position</li> </ul>	<ul style="list-style-type: none"> <li>• Spatial knowledge</li> </ul>

383

384 **4. Implementing human and social behaviors**

385 During evacuation, occupants may refer to their previous knowledge of the building, visual perceptions  
 386 of the floor, and social cues, such as the presence of group members and others’ movements, to determine  
 387 their evacuation routes. This section describes a number of examples to illustrate the capability of  
 388 SAFEgress to simulate some plausible behaviors exhibited by occupants in emergencies. These behaviors

389 include following building features, following familiar exits, group behavior, and herding behavior. In each  
390 example, we discuss the motivation and observation of the behavior, as well as describe the implementation  
391 in the prototype.

392

#### 393 **4.1. Following cues from building features**

394 The spatial arrangement of exit signs with different visual displays are important factors that can affect  
395 the movement pattern (O'Neill, 1991; Johnson and Feinberg, 1997). In situations where the occupants are  
396 unfamiliar with the environment, people rely heavily on the information from the signage to guide their  
397 navigation. Therefore, exit signs should be arranged in a proper way to provide markings of exits and escape  
398 routes in buildings and to assist the occupants in leaving the buildings effectively in case of emergency.

399 In SAFEgress, each agent can decide their navigation based on the perceived floor objects representing  
400 the building features, such as exit signs and doors as described in Section 3.3.2. At each simulation step,  
401 the agents detect visible floor objects and navigate the space according to the direction given by the floor  
402 objects. Figure 7 illustrates the process that an agent navigates the space by perceiving and following the  
403 guidance from the visible floor objects and escaping via visible exits. Initially, the agent chooses to navigate  
404 toward the only visible floor object, which is the door as shown in Figure 7a. After exiting the room via the  
405 visible door, the agent detects new floor objects, which are the two exit signs (Sign 1 and Sign 2). As the  
406 agent detects more than one visible objects, the agent weighs each object according to three criteria: (1) the  
407 object type (namely exits, doors, and signs), (2) the distance of the object from the agent, and (3) the number  
408 of times of prior visits to the object. Because both objects are “sign” objects and have not been visited  
409 before by the agent, the agent chooses to navigate toward the nearest sign, Sign 1, which is indicated in  
410 Figure 7b. Upon arriving at Sign 1, the agent evaluates all visible objects and chooses to go to Sign 2 (Figure  
411 7b). As the agent moves near Sign 2, the agent detects a new floor object, Exit 1; the agent then weighs all  
412 the visible floor objects, chooses to go to Exit 1, and exits the floor (Figure 7c).

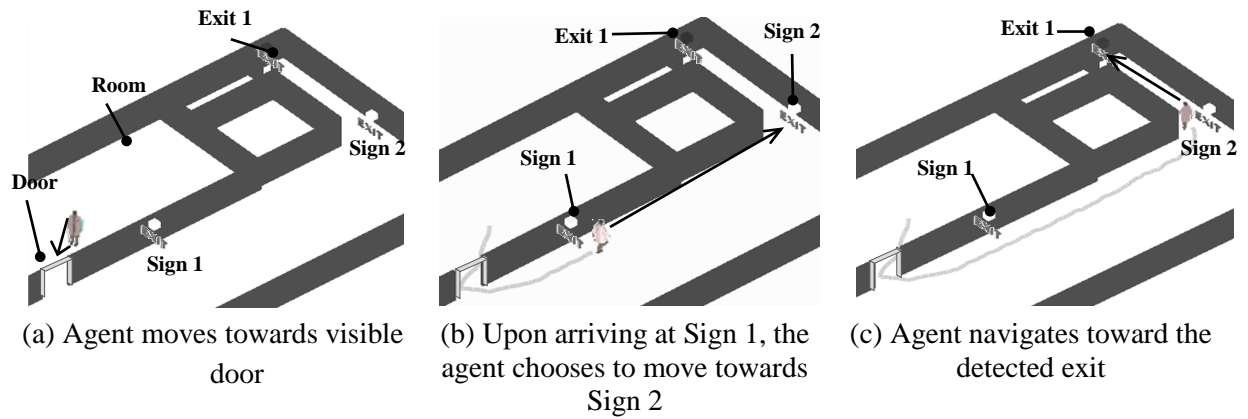


Figure 7. Navigation by following building features

413

414 We further apply SAFEgress to analyze the effects of different exit sign arrangements on egress  
 415 performance. Figure 8 shows the floor layout of a museum which consists of several exhibition halls with  
 416 four main exits (the entrance, the north exit, the west exit, and the café exit). The floor space is populated  
 417 with a total of 360 agents who have medium level of familiarity and have no prior knowledge of exits. They  
 418 exit the floor by following the cue from floor objects. We model different exit sign arrangement with the  
 419 same building model to trigger different navigation patterns of the agents. The effects of signage  
 420 arrangements on evacuation outcomes are compared by: (1) changing the number of exit signs and (2)  
 421 rearranging the orientation of the exit signs.

422

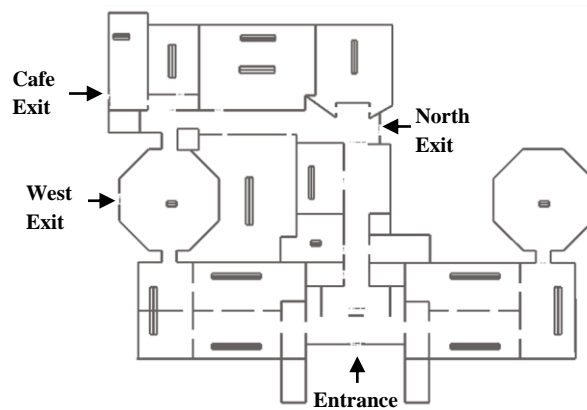


Figure 8. Building layout and exit locations

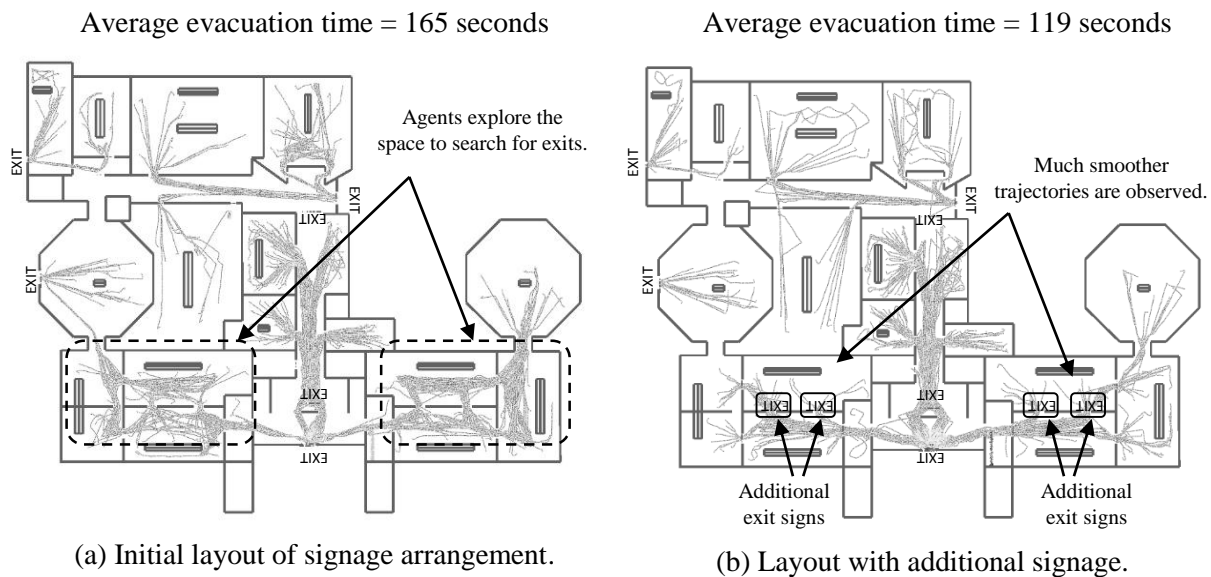


Figure 9. Evacuation patterns of evacuation assuming different signage arrangements

423 The first test studies the effect of additional exit signs on evacuation performance. Figure 9a shows the  
 424 initial layout of exit signs and the trajectories of agents exiting the building. The total evacuation time is  
 425 165 seconds (averaged over 10 simulation runs). As highlighted in the figure, in this initial exit sign  
 426 arrangement, agents take detours and explore the floor before find their way to exit. With additional exit  
 427 signs posted, as shown in Figure 9b, the agents travel with more direct routes, and the evacuation time takes  
 428 119 seconds (a decrease of 28% in time compared to that of initial layout of fewer exit signs).

429

430 The second test illustrates how changing the exit orientation can help direct crowd flow. As shown in  
 431 Figure 9, with the sign arrangement in the first test case, agents tend to exit through the main entrance and  
 432 cause the congestions at the main entrance. As shown in Figure 10, we change the facing direction of an  
 433 exit sign (depicted with rectangular box) in the main aisle. With the proper exit orientation, more agents  
 434 perceived the exit sign and its direction and evacuated through the near exit. As a consequence, the  
 435 evacuation time is 89 seconds, a further improvement of 25%. This example clearly illustrates the

436 importance of appropriately arranging exit sign to effectively guide the crowd for evacuation and alleviate  
437 congestion.

438 Assessing the effectiveness of a signage system is difficult in real setting because this kind of assessment  
439 requires experiments with occupants in the buildings. Modeling salient safety features in egress simulations  
440 allows designers to improve egress performance by analyzing different evacuation patterns as a result of  
441 different signage systems.

442

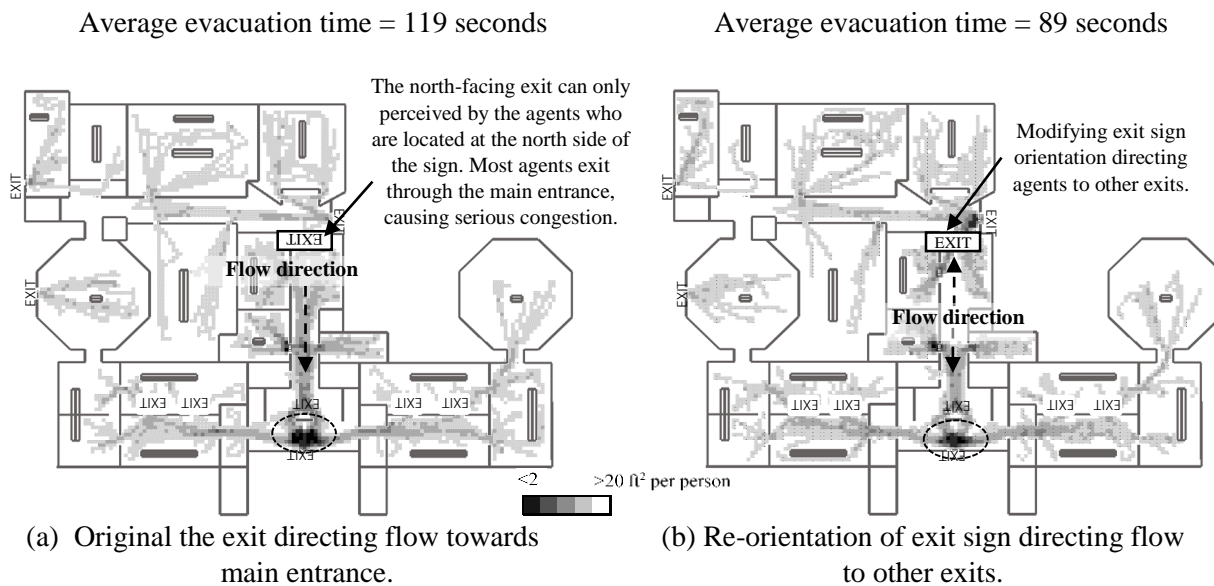


Figure 10. Congestion patterns assuming different signage arrangements

#### 443 4.2. Following familiar exits

444 Occupants choose evacuation routes based on their previous experience and knowledge (Mawson,  
445 2005; Sime, 1983; Tong and Canter, 1985). Occupants who visit the building regularly may have learned  
446 their preferred exits over time or have knowledge of the nearest exits. They may also have evacuation drill  
447 experience from which they learned the instructed evacuation routes in case of emergency. To incorporate  
448 the effect of known exits into agents' route choices, we make use of the agents' static parameter, known  
449 exit(s). We model the "following familiar exits" behavior as follows: prior to the simulation, the user

450 assumes the parameter value of the attribute, known exits, of the agents, indicating that the agents have  
451 knowledge of one or more known exits. During the simulation, the agents query the spatial model with the  
452 known exits and retrieve the shortest paths to the known exits. At the decision making stage, the agents  
453 choose to move to the visible navigation points along the shortest paths to get to their known exits.

454 Figure 11 shows an example floor plan and evacuation patterns resulted from assigning different known  
455 exits to 200 agents. In Case 1, agents have the knowledge of the main entrance and exit through the main  
456 entrance. The arrows in Figure 11a show the emerging crowd flows as agents travel to the main entrance.  
457 In Case 2, agents have the knowledge of all exits and choose to evacuate through the nearest exit given their  
458 initial starting positions. The arrows in Figure 11b show the diverging crowd flows as agents travel to their  
459 nearest exits. Besides the differences in the crowd flow patterns, the assumption of different known exits  
460 also changes the evacuation time significantly. The average evacuation times over 10 simulation runs are  
461 106 seconds and 70 seconds for Case 1 and Case 2, respectively. The longer evacuation time in Case 1 is  
462 due to the longer travel distance and congestion at the main entrance.

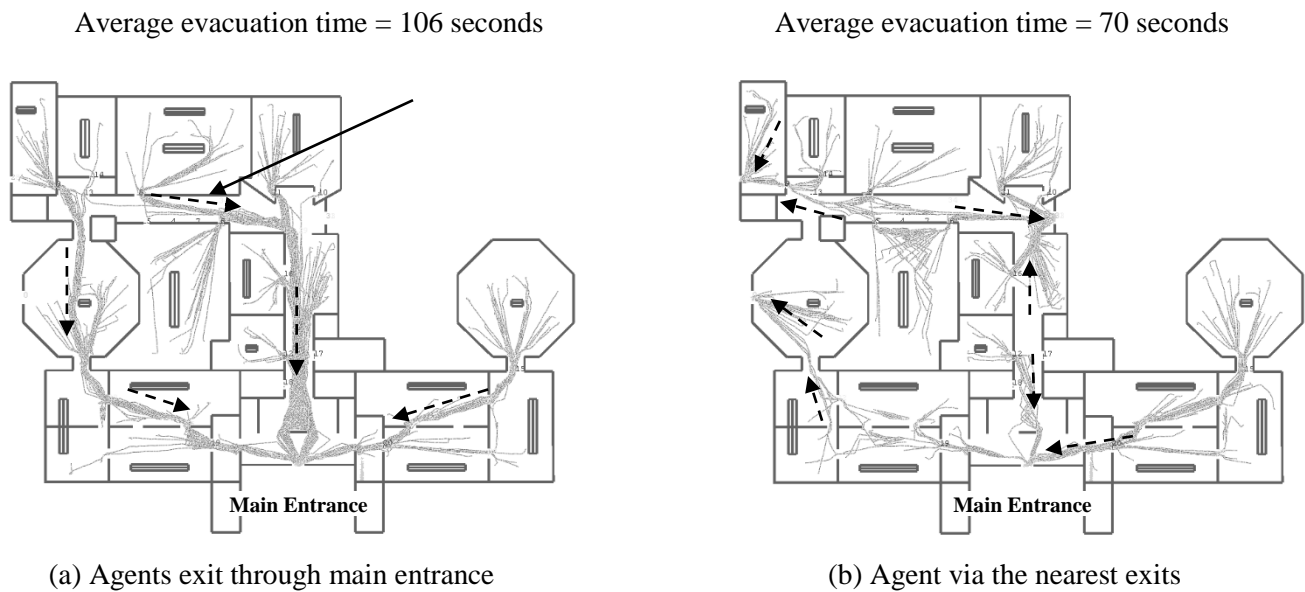


Figure 11. Evacuation patterns with different exit assignments



### 464 **4.3. Navigating with social group**

465 During evacuation, members belonging to a group, such as families and close friends concerned the  
466 safety of their group members, and often seek out and evacuate with the entire group even when evacuation  
467 is urgent (Aguirre et al. 2011; Sime 1983). We model this group behavior using two group-level static  
468 attributes: group separation distance (measured as the desirable physical distance between members) and  
469 group-seeking (measured as the desirable percentage of members that are visible). We assign a low value  
470 (average distance of 4ft to each visible group member) to the group separation distance attribute (i.e. agents  
471 try to maintain close proximity with other group members) and a high value to the group-seeking attribute  
472 (i.e. all group members have to be visible to the group) to simulate agent groups with close relationships.  
473 Figure 12 shows a comparison of the evacuation patterns of agents with and without group affiliations by  
474 varying the group-seeking attribute.

475 In the example showing in Figure 12, we assume all 50 agents evacuate at once. We test the effect of  
476 group affiliation on evacuation patterns. The first case assumes each agent evacuates as an individual  
477 through its familiar exit (which is the nearest exit to the agent). Figure 12a shows the evacuation pattern of  
478 agents without any group affiliation, and the average evacuation time is 29 seconds (averaged over 10  
479 simulation runs). In the second case, we test the effect of group behaviors by assigning all agents with group  
480 affiliation (group size ranges from three to five agents). All groups are assigned with a high group-seeking  
481 value, such that all members in the group have to be visible to each other before the members in the group  
482 start to evacuate. In this case, as shown in Figure 12b, agents pace back-and-forth, and even detour, as they  
483 seek other group members. In this scenario, the average evacuation time increases to 39 seconds (averaged  
484 over 10 simulation runs). The longer evacuation time in the group-seeking scenario is possibly contributed  
485 by longer and indirect routes taken by the agents as they search for the missing group members. By varying  
486 the value assigned to the group-seeking attributes, we can alter the level of desire for the group to look for  
487 other members. Similarly, by adjusting the group separation distance of the social group, we can simulate  
488 different types of groups with different levels of intention to follow other group members. Depending on

489 the initial distribution of the group members and their relationships, group behaviors in egress simulations  
490 affect the evacuation time and the escape routes.

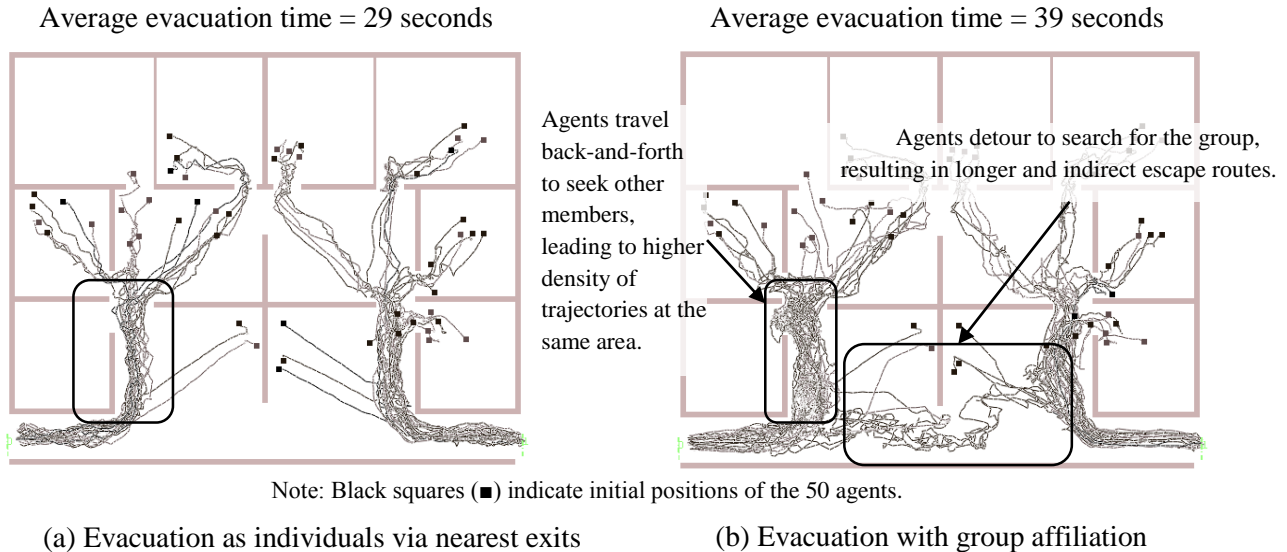


Figure 12. Evacuation patterns with and without group affiliation

491

#### 492 4.4. Following crowds

493 As the first signs of a potential threat are often ambiguous (Tong and Canter, 1985), people may spend  
494 a substantial amount of time to investigate and interact with one another before deciding how to respond  
495 (Sime, 1983). The movement of some evacuees toward different exits provides others with social cues of  
496 the availability of alternative exits. Often, as opposed to moving towards familiar exits, people may follow  
497 social cues and choose the exits preferred by the crowd as they observe others' actions. We model the  
498 "following the crowd" behavior as follows: during the simulation, the herding agent (who is seeking to  
499 follow other agents) perceives the space and detects visible floor objects. At the decision making stage, the  
500 herding agent assesses, for each visible floor object, the number of neighbors who are traveling towards the  
501 floor object. The herding agent chooses the visible floor object with the highest number of neighboring  
502 agents traveling towards because the agent considers the movement of its neighbors as a social cue to  
503 explore potential areas for exits. If there are no visible floor objects that other agents move to, the agent

504 then will adopt other navigation strategies, such as referring to their known exits (as described in Section  
505 4.1) or following the visual cues (as described in Section 4.2).

506 Figure 13 illustrates the differences in agents' trajectories when 100 agents with and without crowd  
507 following behavior. As shown in Figure 13a, when agents follow only visual cues, the usage of the two  
508 exits is about even. When half of the agent population (i.e. 50 agents) exhibit crowd following behavior, as  
509 shown in Figure 13b, one of the exits became more congested. In real situation, the escape routes taken by  
510 the occupants who initiate the evacuation can have an impact on the congestion patterns as other occupants  
511 who are unsure or unfamiliar with the situation will tend to follow the crowd. Herding and overcrowding  
512 phenomena emerge as the crowd triggers individuals to exhibit crowd following behaviors. By including  
513 the perception of crowd movement, our framework captures the emergence of crowd following  
514 phenomenon.



(a) Agents with individual behaviors exiting via the nearest exits

(b) Agents with herding behaviors and with individual behaviors

Figure 13. Evacuation patterns with and without herding behaviors

515

## 516 5. Discussion

517 The building geometry unique to each building and the layout of building emergency features (such as  
518 exit signs and doors) can trigger different navigation decision of the occupants during egress. SAFEgress  
519 allows users to assess different building geometries and egress systems in a flexible manner. Furthermore,  
520 sensitivity analysis on different agent attributes can be conducted in SAFEgress to identify and assess the  
521 impacts of important social factors in different physical and environmental settings, as illustrated in the four  
522 examples presented in this paper. This kind of analysis can give insights to architects, building designers,

523 and facility managers to design user-centric safe egress and improve emergency procedures and training  
524 programs.

525 Our simulation results confirm the needs of incorporating occupants' perception, previous knowledge,  
526 and social behaviors in egress simulation. In our examples, we show that different arrangements of exit  
527 signs, social settings of the agents and prior knowledge and familiarity with the building could trigger  
528 different crowd behaviors and crowd flow patterns. By embedding individuals into groups, our model has  
529 the capabilities to model occupant behaviors such as the spreading of information within social groups and  
530 crowds (Rydgren 2009; Hoogendoorn et al. 2010) and the role of authorities (Kuligowski 2011). In broader  
531 terms, we see our approach to modeling social behavior to be in line with recent efforts in computational  
532 social science to capture emerging social behaviors using computer-simulation and large datasets made  
533 available through digital technology and new forms of communication (Lazer et. al., 2009). The described  
534 platform represents a step forward toward incorporating social science knowledge of social interactions into  
535 engineering models that capture human behaviors.

536

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542

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