An Agent-Based Simulator for Indoor Crowd Evacuation Considering Fire Impacts

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Abstract

Fire emergencies impose significant threats to building occupants. During evacuation, fire has significant impacts on evacuees' behaviors, by e.g., changing their route availability, disturbing their perception of the environment due to reduced visibility, impairing their mobility that is usually associated with severe injuries, and causing significant mental stress that may lead to complicated and unpredictable navigation decisions. Despite the detrimental effects of fire on crowd evacuation, most existing building evacuation simulation models and tools do not account for the impacts of fire on the evacuation process; at most they rely on oversimplified assumptions and simulation settings. In this study, a new fire evacuation simulation model, named FREEgress (**F**ire **R**isk **E**mulated **E**nvironment for E**gress**), is developed to simulate the dynamic influences of heat, temperature, toxic gas and smoke particles on evacuees' mobility, navigation decision making and health conditions. FREEgress (1) introduces evacuee agents who are aware of and able to assess the fire hazards, and can make fire risk-informed navigation decisions; and (2) models the interactions between evacuee agents and the dynamic fire emergency environments and the consequent evacuation process. The verification of FREEgresss is conducted by comparing its simulation results with two existing simulation tools, SAFEgress and FDS+Evac. In addition, a case study using FREEgress is carried out to simulate the evacuation in a museum for 30 different fire emergency scenarios. The simulation results are analyzed to assess the impacts of three important factors, namely initial fire location, evacuation delay time and evacuee behavior, on the evacuation process and evacuation outcomes. The case study demonstrated the potential value of FREEgress to support both the safety design of new buildings and maintenance

and emergency management of constructed facilities.

Keywords: building emergency, fire evacuation, indoor, agent, multi-agent simulation, fire hazard, fire impact, FREEgress.

1. Introduction

Fire emergencies impose critical threats to buildings and their occupants. Public fire departments across the U.S. attended 499,000 fires in buildings in 2018, which caused 2,910 deaths and 12,700 injuries [1]. During fire emergencies, hazardous fire conditions and unsuccessful evacuation attempts can expose occupants to significant risks [2,3]. Evacuation simulation is an effective approach to reproduce occupants' evacuation behavior during building fire emergencies, which is fundamentally important for advancing the understanding about occupants' navigation decision-making during evacuation, and for developing appropriate measures to facilitate the evacuation process and hence reduce the risks occupants may be faced with [4].

There is an increasing volume of literature in recent decades that has focused on developing models for simulating crowd evacuation during building fire emergencies. These models can be broadly categorized into three groups based on simulation techniques, namely particle system models, cellular automata models and agent-based models [5]. A typical example of particle system models is the social force model proposed by Helbing [6]. Although particle system-based simulations can successfully simulate typical phenomena (such as panic) and observe self-organization behaviors (e.g., faster is slower and mass behavior) in pedestrian dynamics, they cannot reproduce subtleties of individual behaviors (e.g., walking in pairs) [7]. Moreover, they neglect to consider occupants' decision making and oversimplify their navigation process [8]. Cellular automata models are widely adopted by many commercial simulation tools, such as Building EXODUS [9], Simulex [10], and CAFÉ [11]. These models reproduce many collective behaviors (such as clogging and arching) and are suitable for large-scale computer simulations, but they have limited realism in representing occupants' decision making and dynamic environment change [7]. Nor can these models represent the impact of pedestrians' injuries or that of high-density crowds [8]. Agent-based models consider each evacuee as an autonomous agent, who can perceive surrounding environments, exchange information with other agents, make informed evacuation decisions, and implement evacuation strategies accordingly. Examples of agent-based models for crowd evacuation include Vicrowd [12], HiDAC [13], MASSEgress [14], SAFEgress [15] and Pathfinder [16]. These models can not only simulate the intelligent and heterogeneous agents and environments but also capture emergent phenomena (such as crowd congestion) and complex human behaviors (such as competitive behavior, queuing behavior and herding behavior) [4]. Therefore, these models have been popularized in the latest literature. While various existing agent-based models have incorporated many principles of human behavior and significantly advanced the efficacy of building fire evacuation simulation, most existing models have thus far ignored the impacts of fire hazards on human behavior and consequently on the outcomes of evacuation. Fire has significant impact on evacuees' egress behaviors in several aspects [3,17]. First, evacuees, by instinct, would choose a route that can avoid high temperature and heat; second, heavy smoke can reduce the visibility and therefore cause occupants to slow down, while the toxic gases can impair occupants' mobility and even lead to severe injuries and failure of evacuation. In extreme cases, fire hazards can cause significant mental stress that may lead evacuees to make complicated and unpredictable navigation decisions.

Despite the significant effects of fire in crowd evacuation, most existing building simulation models and tools do not account for these impacts or rely on oversimplified assumptions and simulation settings. The lack of realistic simulation of fire impacts is especially critical. Modeling fire impacts is a challenging issue considering the fact that fire and smoke develops and spreads, and their influence on occupants is highly dynamic and spatiotemporal-specific. Although several commercial or academic simulation tools have attempted to incorporate the impacts of fire in evacuation simulation, including Building Exodus [9], FDS+Evac [18], FireGo [19] and AIEval [20], fire impacts are highly oversimplified and usually underestimated in these tools, owing to the particle system or cellular automata-based structure of these tools [21] or their simplified qualitative rule-based reasoning mechanism [7]. Failure to appropriately account for the fire impacts has largely prevented fine-grained modeling of evacuees' navigation decision-making and behaviors, leading to inaccurate prediction of evacuation process and outcomes.

Motivated by this gap, this study aims to develop a new simulation model, FREEgress (**F**ire **R**isk **E**mulated **E**nvironment for E**gress**), to incorporate the various impacts of fire on evacuees into the evacuation simulation, by (1) introducing evacuee agents, who are aware of and able to assess the fire hazards, and can make fire risk-informed navigation decisions; (2) modeling interactions between evacuee agents and the dynamic fire emergency environments and the consequent evacuation process. FREEgress inherits major features of SAFEgress [15], its earlier version which is proven effective in simulating both human and social behaviors in the evacuation process [21]. By appropriately accounting for fire impacts in the agent-based modeling of fire evacuation, FREEegress aims to achieve more realistic and fine-grained simulation of evacuees' navigation decision-making and navigation behaviors by incorporating dynamic fire impacts, and ultimately achieve more accurate simulation and prediction of crowd evacuation processes and outcomes for various building fire emergency scenarios.

2. Fire Impact on Evacuees

Fire hazards (e.g., heat and high temperature, toxic gas and smoke) impact evacuees physiologically and psychologically during fire emergency evacuation [17]. Specifically, these fire hazards influence evacuee's motion speed, health, decision making and navigation, which are important for determining the outcomes of their evacuation tasks to a large extent. Based on a thorough review of relevant literature, the fire impacts are summarized as follows.

Heat and high temperatures during fire emergencies can significantly diminish evacuees' health conditions. The tenability limit for the skin is 2.5 kw/m^2 [17]. At this limit, people can tolerate up to 5 minutes, while above this limit people may be burned in just a few seconds. Purser and McAllister [17] also pointed out that the high temperature poses a major threat to evacuees in fire emergencies, which can result in heat stroke, skin burns and respiratory tract burns. Exposure to temperatures above 120 ℃ for minutes may quickly immobilize an individual and eventually lead to fatality. Exposure to environments with slightly lower temperatures but high humidity may also cause heat stroke. Simms and Hinkley [22] investigated the tolerance time of people under different temperatures. They pointed out that under dry air, when the temperature reached 110 ℃, people's tolerance time was 25 minutes, after which people would be faced with fatal risks. This tolerance time would quickly drop to 3 minutes when the temperature was increased to 180 ℃.

Toxic gases produced by fire can also greatly harm evacuees' health conditions. Fire combustion generates mainly six toxic gases, including carbon monoxide (CO), carbon dioxide (CO2), hydrogen cyanide (HCN), hydrogen chloride (HCl), hydrogen bromide (HBr) and nitrogen dioxide (NO2), among which CO is the most deathful [23]. When CO is absorbed in the human body, it combines with hemoglobin. As a result, red blood cells lose their ability to transport oxygen, which leads to hypoxia and death. Several models have been developed in the literature to assess the impact of toxic gas hazards on humans. The N-gas model [23], developed by the National Institute of Standards and Technology (NIST), assumes that the toxicity is mainly caused by the superposition of toxic gases from the combustion products. The model considers the effects of the above six toxic gases. By extending the N-gas model, Babrauskas et al. [24] developed the FED (fraction effective dose) model, which could account for the interactions between CO2 and CO/O2 to better describe the toxic effect. Moreover, Stuhmiller et al. [25] proposed a quantitative mathematical model, the Toxic Gas Assessment Software (TGAS), to estimate the probability of human body disability based on the concentration of toxic gases in the alveoli and the absorption coefficient.

The smoke that spreads at fire emergency scenes can significantly slow down their motion speed [26]. The extinction coefficient is often used to reflect the smoke density [27]. Through a large number of experiments, Jin and Yamada [27] pointed out that the motion speed of evacuees would be reduced as the extinction coefficient increased, and it would be reduced rapidly when the extinction coefficient increased to 0.5/m. Under heavy smoke, as Jenson [28] reported, people's motion speed is limited to 0.2m/s~0.5m/s. Smoke also lowers evacuees' visibility to decrease their motion speed. Smoke can also significantly impair the visual range of evacuees and increase the difficulty of evacuation. Experiments have shown that under low visibility conditions in indoor environments, people would tend to walk along walls, and their motion speed would be lower than that under normal conditions (Purser and McAllister 2016). Jin and Yamada [27] pointed out that during a building fire evacuation, for people who were familiar with the indoor space, a minimum visual range of 4 meters was required for them to evacuate successfully, whereas for those who were not familiar with the space, a minimum visual range of 13 meters was needed. Yet, Rasbash [29] contended that a visual range of 10 meters should be guaranteed, regardless of the familiarity with the surroundings.

Apart from that adverse impacts on evacuees' health conditions, fire hazards can also impact evacuees' decision making and navigation during fire emergencies [14]. For instance, evacuees' perceptions about surrounding environments and neighboring evacuees may be hindered when their visibility is narrowed by smoke [30], which would cause difficulties for them to find adjacent navigation points. Evacuees may also become stressful when facing fire hazards, which would decrease their judgment ability. As a result, evacuees may tend to follow the crowd flow, which sometimes causes unbalanced use of exits and increases the total evacuation time [31], or even results in crowding and trampling. In addition, for fire emergency scenes, Purser and McAllister [17] defined safe areas as places where the temperature is below 120 ℃, the heat flux is less than 2.5 kw/m^2 and the oxygen concentration is higher than 12%. As fire hazards develop and spread during fire emergencies, the boundaries of safe areas change, which dynamically impact evacuees' navigation strategies and may force them to find alternative routes as they try to stay within the safe areas.

3. FREEgress

3.1 System architecture

FREEgress is a crowd evacuation simulation model, which extends its earlier version, SAFEgress [15], by incorporating dynamic impacts of fire hazards on evacuees to achieve more realistic and accurate simulation of evacuees' behaviors and indoor emergency evacuation process. Figure 1 illustrates the overall system architecture of FREEgress. Three key modules are Global Database, Crowd Simulation Engine and Agent Behavior Models Database. This model also includes a few supporting sub-modules, including Situation Data Input Engine, Geometry Engine, Event Recorder, Population Generator and Visualizer. These modules are mostly inherited from SAFEgress but a number of them (as illustrated with dashed boxes in Figure 1) have modified functions. In addition, FREEgress can interact with Pyrosim [32], which is a graphical user interface for fire hazards modeling software Fire Dynamics Simulator (FDS) [33] and visualization software Smokeview [33], to enable exchanges of fire data and trajectory data. This new function is illustrated with dashed arrows in Figure 1. All FREEgress modules and their functions are further explained in the remainder of this section.

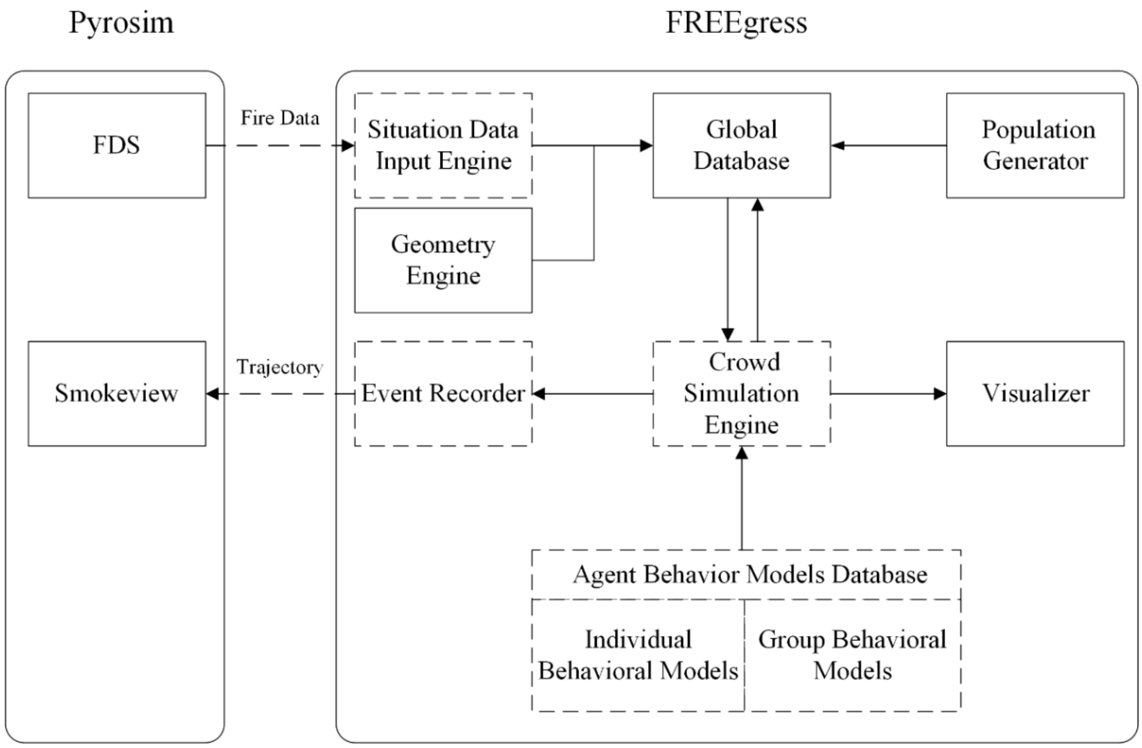


Figure 1: Architecture of FREEgress

In addition, an overall phase list of FREEgress is shown in Figure 2, which illustrates how FREEgress works. First, for any given building under investigation, its floor plan is imported into the Geometry Engine to generate a virtual environment. Second, fire simulation settings, such as heat release rate (HRR), fire growth rate and fire location, are defined in Pyrosim [32], and fire data generated by the FDS model [33] are imported into the Situation Data Input Engine. Third, a 2-D grid of uniformly sized square cells is cast over the virtual environment and a navigation map is generated by the Geometry Engine based on the grid cells. Next, different types of cue objects such as an alarm and fire or strobe light, and their locations are set by users using the Situation Data Input Engine. Meanwhile, the number and location of agents, and their behavior type and delay time are also defined by users using the Population Generator and the Agent Behavior Models Database, respectively. The above settings are all stored in Global Database. Then, evacuation simulations are carried out by the Crowd Simulation Engine, which generates a number of simulation outputs, including agents' evacuation time, speed, trajectory, health conditions, fatalities and route availability. These outputs are stored in the Event Recorder and illustrated to users by the Visualizer. Finally, fire data and agents' evacuation trajectories are imported into Pyrosim, and agents' evacuation processes are synchronously visualized and animated using Smokeview [33].

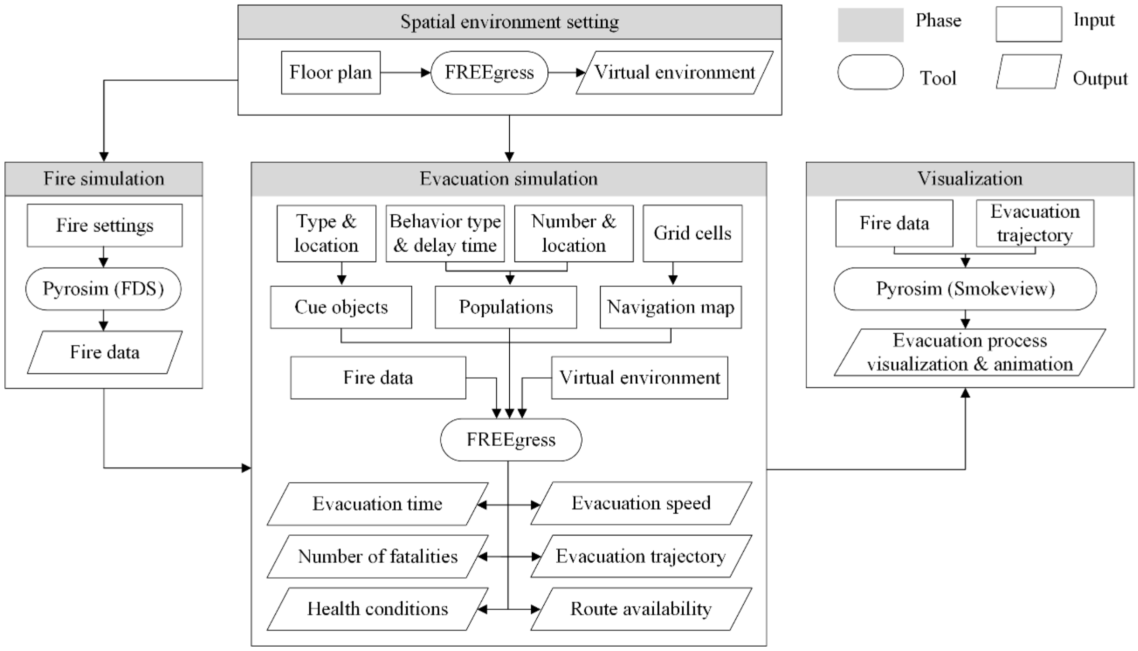


Figure 2: Phase list of FREEgress

3.2 Representation of the spatial environment

Building layout and building features (such as doors) can significantly influence occupants' evacuation route choices during fire emergencies [21]. In FREEgress, a spatial model of the indoor environment set by users is used to represent the building layout, which is stored in the Geometry Engine. The building layout is a 2D projection of building obstacles (such as walls and furniture) on the horizontal floor. The agents equipped with simulated vision capability can detect the obstacles and avoid colliding with them. However, the agents cannot see or pass through the obstacles.

In fire emergencies, occupants often use building features (such as exits, doors and exit signs) to guide their evacuation. These features are represented as navigation objects in FREEgress. Each object is defined by its type, location, orientation, as well as directional information if applicable (e.g. exit sign). These characteristics can be defined by users. In FREEgress, three types of navigation objects are defined, namely exit, door and exit sign. Each exit represents an outlet of the building. When an agent arrives at an exit, its evacuation task is considered completed. The agent can move from one room to another by crossing a door. An exit sign is used to indicate evacuation routes or directions such as "forward" and "turn left". Exits, doors and exit signs, which do not represent all possible building safety features, are the most significant features pertaining to egress design and have a major impact on people's evacuation decisions [21]. In addition, other types of navigation objects can also be defined if needed.

3.3 Simulation of fire hazards and emergency cues

Fire hazards, including heat, high temperature, smoke particles and various toxic gases, can be produced during fire incidents, which would greatly diminish evacuees' motion speed and health conditions [17,18]. To assess the development of these fire hazards and account for their impacts, the following five types of spatiotemporal data are collected from fire simulations in Pyrosim: temperature, heat flux, fractional effective dose (FED), fractional irritant concentration (FIC) and extinction coefficient. These data correspond to different impacts on evacuees, which are further discussed in Section 3.4. In FREEgress, the floor plan is discretized into a grid of uniform cells of 1.524 m by 1.524 m (equivalent to 25 sqft). The fire status of each cell is represented by the five types of fire data in the center point of each cell. To measure and record the values of the above five parameters in the fire simulation process in Pyrosim, a thermocouple and four gas-phase devices are placed at the center of each cell to obtain the five types of data, respectively. These data are measured at height Z=1.5 m, which is the approximate height of people's mouth and nose. The recording interval of these devices was set to be one second over the entire fire simulation process in Pyrosim. The data generated by Pyrosim are converted using Matlab to a format that can be read and parsed automatically by FREEgress. In FREEgress, the fire data of each cell is updated every second, consistent with the time granularity of the fire data. The import of fire data is implemented using the Situation Data Input Engine.

During fire emergencies, occupants can get access to the cues that trigger the evacuation process [21]. In FREEgress, audio cue objects such as an announcement and an alarm and visual cue objects such as fire or strobe light are modeled. These objects are defined by their type, source location, effective range, active period during the simulation and reaction time. The reaction time refers to the required time lag from when an occupant perceives the cue to when the occupant takes evacuation actions, assuming that the occupant has no prior experience of the cue. The triggering condition of the audio cue is that an agent is within the effective range of the cue. The triggering conditions of the visual cue are that an agent is within the effective range of the cue and the line of sight between the agent and the location of the cue object is not blocked by any obstacles.

3.4 Agent representation of evacuees

Occupants that evacuate from fire emergency scenes are modeled as agents in FREEgress. Each agent is configured based on a set of static and dynamic attributes, which can be categorized into the individual and group levels, as summarized in Table 1.

Table 1: Attributes of evacuee agents in FREEgress

Attributes	Individual level	Group level
Static attributes	▪ Physical profile [34] ▪ Known exits [35-38] ▪ Cue awareness factors [35-38]	▪ Group compliance [39,40] ▪ Group influence [39,40] ▪ Group separation tolerance [39,40]
Dynamic attributes	▪ Visible navigation objects [41] ▪ Emergency cues [42-43] ▪ Fire hazards perception [17] ▪ Urge level [44] ▪ Physiological profile [17] ▪ Selected behavior [44-46] ▪ Navigation goal [47,48] ▪ Navigation point [47,48] ▪ Spatial position [47,48] ▪ Spatial knowledge [47,48]	▪ Visible group members [49,50] ▪ Neighboring agents [49,50]

Note that each attribute has its own range, and users can define different types of agents by assigning different values to the attributes [44]. For instance, the value of cue awareness factor ranges from 0.01 (indicating highest cue awareness hence the shortest delay time) to 2.0 (indicating lowest cue awareness hence the longest delay time). For brevity, details of all attributes can be found in [44] and are not further elaborated in this paper.

At the individual level, an agent is defined by its physical profile, which includes attributes such as age, gender, body size and personal space [34]. The familiarity with the building environment is defined by a set of known exits [35-38]. The agent's emergency experience is determined by cue awareness factors [35-38]. At the group level, a social group is defined by group compliance [39, 40]. The agent adopts group behavior only when the group compliance is high. The group influence determines the agent's influence on other members in the same group [39, 40]. The group separation tolerance, which is used to detect whether an agent is too far from the group, describes the agent's allowable maximum distance away from other visible group members [39, 40].

Occupants' wayfinding behaviors during fire emergencies are the result of complex cognitive processes [45]. Based on the investigation of human wayfinding behaviors during fire emergencies in a number of prior studies [37, 44, 45, 46], the agent' behavior in FREEgress is modeled with a four-stage behavior cycle, namely perception - interpretation - decision-making - execution, that supports structured representation and computation of the agent behavior. As illustrated in Figure 3, an agent's dynamic attributes are updated during this recursive process. At the perception stage, the agent perceives five types of information that are found to be important for their wayfinding decisions in prior research: (1) visible navigation objects such as exits, doors and exit signs [41]; (2) visible group members [49,50]; (3) neighboring agents [49,50]; (4) emergency cues such as alarm and strobe lights [42,43]; and (5) fire hazards such as heat, temperature, smoke and toxic gas [17]. At the interpretation stage, based on the perceived danger, cue objects and urges of its social group and neighboring groups, the agent updates its visibility, motion speed, health conditions and internal urge. The urge level, which has a value ranging from 0 (low urge) to 1 (high urge), is a measurement of the agent's urgency to undertake or modify the evacuation actions [44]. The visibility, motion speed and health conditions determine the physiological status of the agent [17]. At the decision-making stage, the agent first checks its individual behavior attribute, and determines whether to adopt perception-based behavior, which means the agent perceives the surrounding environments only based on visible navigation objects, or knowledge-based behavior, which means the agent is familiar with the environment such as the location of exits [45-46]. Then, the agent reasons through the group behavior. If its group compliance attribute is configured to have a high value, its behavior type changes to the following-leader behavior, which means the agent follows a leader in the group to evacuate, regardless of its individual behavior. The above behaviors are pre-defined and stored in the Agent Behavior Models Database. At the end of the decision-making stage, the agent updates its selected behavior, navigation goal and navigation point. The navigation goal is the final target of the evacuation, such as an exit, and might not be in the agent's line of sight [47,48]. The navigation point is the target position of the intended next movement and is visible to the agent [47,48]. The navigation point determines the agent's intended motion direction. At the execution stage, the agent conducts locomotion to update its spatial position. As the agent moves, it also updates its spatial knowledge, which keeps track of the areas previously visited.

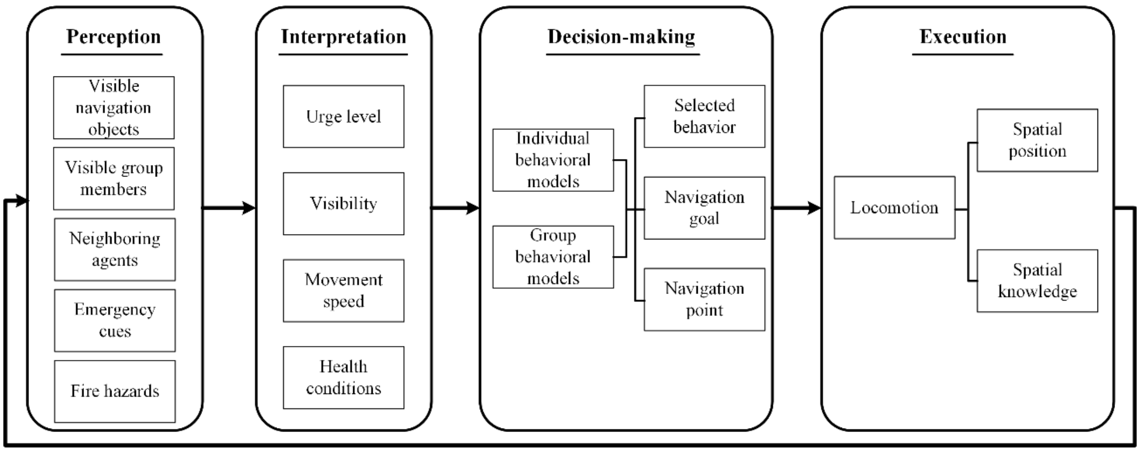


Figure 3: Decision-making process of agents during fire emergencies

3.5 Modeling of fire impacts on evacuees' physiology

Fire hazards can impact evacuees physiologically, by lowering their motion speed and impairing their health conditions. These impacts are quantitatively assessed and modeled in FREEgress using the Crowd Simulation Engine, as explained below.

3.5.1 Fire impacts on motion speed

Fire hazards, particularly the smoke, can significantly slow down occupants' motion speed and hinder their evacuation [17]. The extinction coefficient is usually used to measure the smoke density [27]. In the SFPE Handbook of Fire Protection Engineering, Purser and McAllister [17] proposed that irritating smoke and non-irritating smoke have different impacts on occupants' speed, and an agent's maximum motion speed during normal conditions equals 1.2 m/s. For non-irritating smoke conditions, the relationship between the agent's motion speed (V, m/s) during fire emergencies and the extinction coefficient (K, $1/m$) follows Equation (1) [17]:

$$\mathrm{V} = -0.1733 \ln K + 0.6933 \tag{1}$$

For irritating smoke conditions, the relationship between the agent's motion speed (V, m/s) during fire emergencies and the extinction coefficient (K, $1/m$) follows Equation (2) [17]:

$$\mathrm{V} = e^{-(1000\mathrm{FIC}/160)^2} + (-0.2\mathrm{FIC} + 0.2) \tag{2}$$

where FIC is a relatively effective concentration for irritating gases, the value of which can be acquired by setting a gas-phase device at the location of interest in Pyrosim.

Considering the different motion speed of the agents during normal conditions for different ages and genders, their motion speed during normal conditions were normalized using a normalization coefficient. The normalization coefficient of smoke obscuration' effect on moving speed (f_{smoke}) and the normalization coefficient of smoke irritancy' effect on the moving speed (f_{irr}) can be obtained as Equation (3) and Equation (4) [17], respectively:

$$f_{smoke} = \frac{-0.1733 \ln K + 0.6933}{1.2} \tag{3}$$

$$f_{irr} = \frac{e^{-(1000\mathrm{FIC}/160)^2} + (-0.2\mathrm{FIC} + 0.2)}{1.2} \tag{4}$$

where f_{smoke}= 1 for irritating smoke conditions, and f_{irr}=1 for non-irritating smoke conditions.

Combining the influence of smoke obscuration and irritancy, the motion speed of an agent during fire emergencies can be calculated based on Equation (5):

$$\mathrm{V} = (1 - (1 - f_{smoke}) - (1 - f_{irr})) \times V_{nor} \tag{5}$$

where V_{nor} is the motion speed of an agent during normal conditions.

3.5.2 Fire impacts on health

The adverse impacts of fire hazards on evacuees' health are mainly caused by heat and toxic gases [17]. In FREEgress, a health value is assigned to each agent to assess its health condition. The initial health value is set at 1, which will be reduced when the agent is imposed to fire hazards. If the health value is reduced to 0, it indicates that the agent has lost its escape capability and a fatality occurs.

Heat-related risks to human health are mostly related to two forms of heat transfer, including heat radiation and heat convection [17]. Accordingly, the adverse impacts of fire hazards on the health value of the agents are modeled in FREEgress as follows.

For heat radiation, the tenability limit for the skin is approximately $2.5kw/m^2$, below which people can tolerate for several minutes, while at this limit and above skin can be burned in just a few seconds [17]. In general, the relationship between the time to escape incapacitation (t_{rad}, min) and the heat flux (q, kw/m^2) follows Equation (6) [17]:

$$t_{rad} = \begin{cases} r/q^{1.33}, & q < 2.5\,kw/m^2 \\ 0, & q \geq 2.5\,kw/m^2 \end{cases} \tag{6}$$

where r $=10(kw \cdot m^{-2})^{1.33} min$. For heat convection, the time to incapacitation of agents is determined by the environment temperature. Exposure to temperatures above 120 ℃ for 5 minutes is a significant cause of burn injury and can eventually lead to fatality, while a victim exposed to temperature less than 120 ℃ is unlikely to get burned but may also suffer heatstroke after a long exposure (e.g. exceeding 15 min) [17]. The relationship between the time to escape incapacitation (t_{conv}, min) and the environment temperature (T, ℃) follows Equation (7) [17]:

$$t_{conv} = 5 \times 10^7 T^{-3.4} \tag{7}$$

Considering the impacts of both heat radiation and heat convection, the health damage caused by heat (FED_Heat(Δt)) can be calculated based on Equation (8) [17]:

$$\text{FED\_Heat}(\Delta t) = \int_{t_1}^{t_2} \left(\frac{1}{\mathrm{t}_{rad}} + \frac{1}{\mathrm{t}_{conv}}\right) \Delta t \tag{8}$$

where $\Delta \mathrm{t} = \mathrm{t}_2 - \mathrm{t}_1$. Meanwhile, the FED model [24] is the most commonly used model to evaluate the escape incapacitation and lethality for humans infected by toxic gas. Agents' health condition can be reflected by FED value. When the cumulative value of FED exceeds 1, it indicates the agent loses its escape capacity. The relationship between FED value of an agent and the time that the agent has been exposed to fire hazards follows Equation (9):

$$\mathrm{FED}(\Delta t) = \mathrm{FED}(t_2) - \mathrm{FED}(t_1) \tag{9}$$

where $\Delta t = t_2 - t_1$, FED(Δt) is the health damage caused by toxic gas during Δt time, FED(t_1) is the FED value at time t_1, and FED(t_2) is the FED value at time t_2.

Combining the effect of heat and toxic gases, the health condition of an agent at time t (Health(t)) in FREEgress can be calculated based on Equation (10):

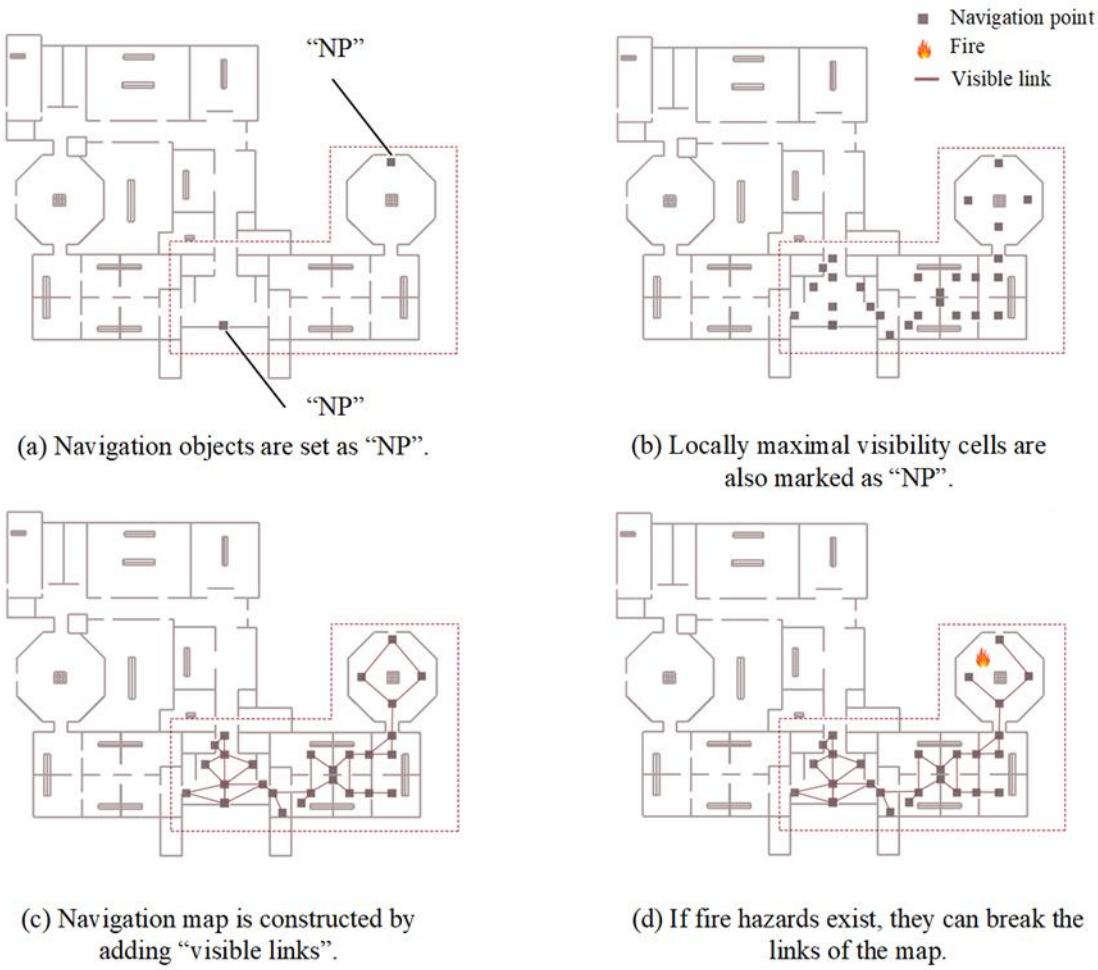
$$\mathrm{Health}(t) = 1 - \mathrm{FED}(t) - \mathrm{FED\_heat}(t) \tag{10}$$

In Pyrosim, the FED value can be acquired by setting a gas-phase device at the location of interest. In this study, the initial FED value (FED(0)) is 0. Then the FED value at time t is FED(t) and the initial health of an agent is defined as 1 at t = 0 s.

3.6 Modeling of fire impacts on evacuees' navigation strategy

The navigation strategy of agents in FREEgress were inherited from SAFEgress, which incorporated relevant studies in the fields of environmental psychology [47] and robotic navigation [48], with additional consideration of the impact of fire hazard. In SAFEgress, agents always choose to move to a direction that allows them to maximize new spatial information about the environment in the next position. To model this strategy, the concepts of navigation point (denoted as "NP") and navigation map are introduced (Figure 4). The NPs, which are points with locally maximum visibility, represent building safety features (such as exits, doors and exit signs) that have major impacts on people's evacuation decisions [44, 48]. The NPs are computed as follows: a continuous space is divided into 2D grid cells. The navigation objects (e.g., exits, doors and exit signs) are set as initial NPs (Figure 3(a)). Then, the visible area of each cell's center is computed as the cell's visibility. If the visible area of a cell is larger than that of all adjacent cells, then the center of the cell is marked as a NP (Figure 3(b)). The navigation map is constructed by adding edges to link all pairs of NPs that are visible to each other (Figure 3(c)). However, when fire hazards exist between a pair of cells, where the heat flux is more than 2.5 kw/m^2 or the temperature exceeds 120 Celsius [17], then the edge between these two NPs is removed (Figure 3(d)), which reflects that fire hazards can limit the agents' route options at every move, and reshape their navigation strategy. It is noted that the navigation decision of the agents is mainly determined by the behavior type of the agent (such as perception based vs knowledge based vs follow familiarity). Even with the same NPs and navigation map, the navigation route of the agents can be entirely different if the agents assume different evacuation behaviors.

When multiple NPs are visible from the current position, agents with different types of behavior have different navigation strategies. Agents with knowledge-based behavior choose the NP that is closer to known exits in their visible area. Agents with perception-based behavior choose the NP according to environmental cues, while avoiding visiting the NPs that have been visited before. Agents adopting following-leader behavior choose a leader agent as a NP, and the leader agent adopts knowledge-based behavior. The leader agent will move towards the group member agents, who could be family members or close friends, when their distance exceeds a certain tolerance [21,39]. Lastly, after the agents choose a NP, they move to the NP, and memorize the areas they have visited.



(a) Navigation objects are set as "NP".

(b) Locally maximal visibility cells are also marked as "NP".

(c) Navigation map is constructed by adding "visible links".

(d) If fire hazards exist, they can break the links of the map.

Figure 4: Procedure for generating a navigation map within the dotted box area

3.7 Synchronous visualization of fire spread and evacuation

FREEgress can visualize the spreading of fire hazards and the evacuation of agents synchronously by linking to Smokeview. Specifically, FREEgress records the trajectory of every agent and outputs a text file (txt), which contains agent ID and timestamped 2D coordinates. A Matlab program is developed to convert the trajectory file into a specified format file (txt), which contains agent ID, the timestamp, number of agents and 2D coordinates. A Fortran program is developed to read and extract these data and generate an unformatted file (*.prt5), which can be loaded to the Smokeview to visualize the spreading of fire hazards (e.g. fire and heat) and the movement of the agents synchronously, as illustrated in Figures 5 (showing spreading of smoke) and 6 (showing temperature change).

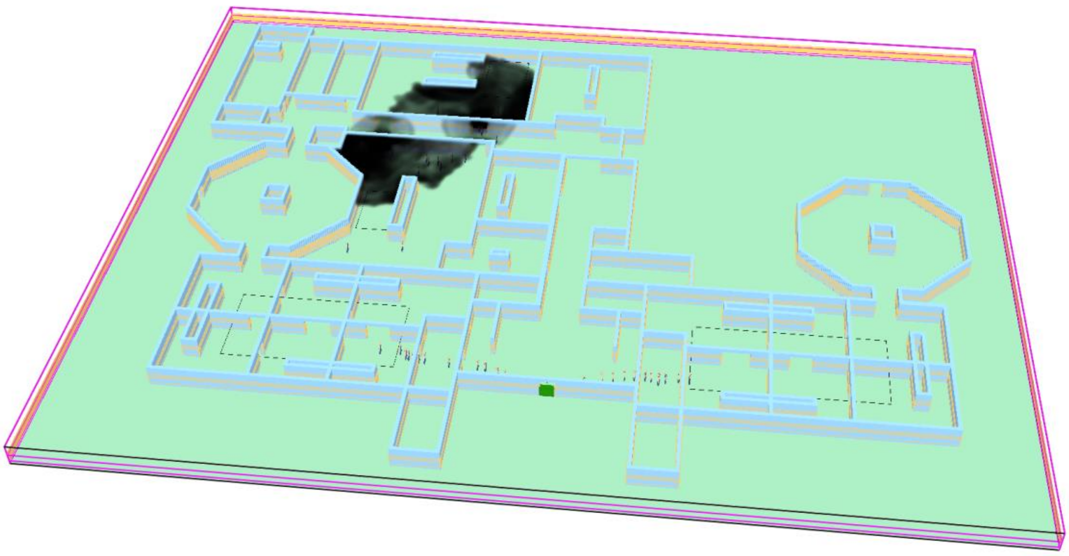


Figure 5: Synchronous visualization of spreading of smoke and movement of agents

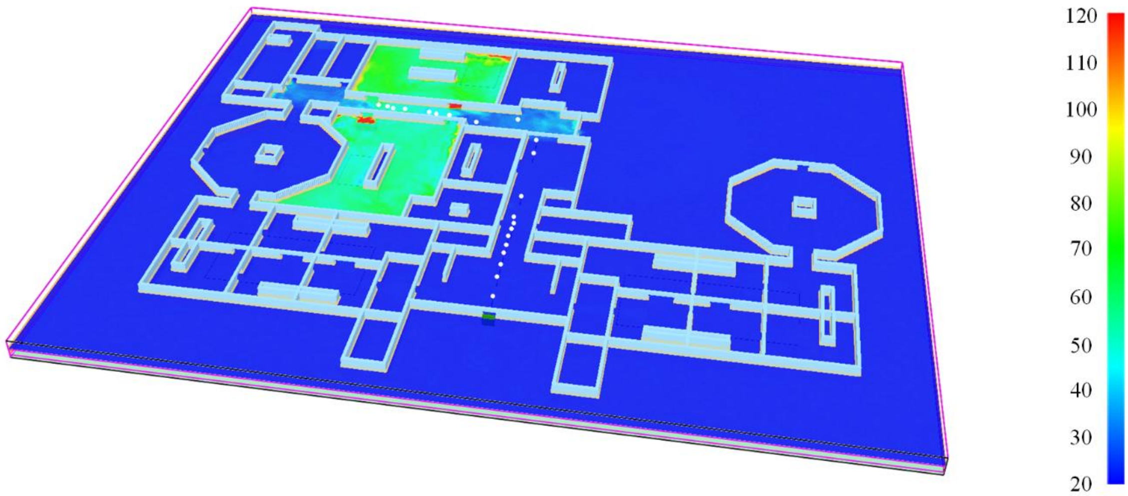


Figure 6: Synchronous visualization of temperature change and movement of agents

4. Model Verification Methodology

4.1 Verification rules

The general rule adopted for verifying the proposed FREEgress model is that, when FREEgress and existing verified tools are used to simulate the same set of fire emergency scenarios, FREEgress can be considered as verified 1) if no significant differences exist between their respective evacuation outcomes; or 2) if significant differences in their respective evacuation outcomes are observed, and the differences are reasonable owing to the inherent differences between FREEgress and other tools.

Specifically, to verify the efficacy of FREEgress, the following two hypotheses were made and tested in this study. Hypothesis I: Since FREEgress was developed by extending SAFEgress with new functions that incorporated fire impacts, it was hypothesized that the simulation results reported by FREEgress would be largely consistent with those reported by SAFEgress when the scale of fire was small, but the discrepancies would increase as the scale of fire increased and the fire impacts became significant. Additionally, FDS+Evac is a typical commercial solution for fire evacuation simulation. It is one of the few existing tools that can partially account for the physiological impacts of fire hazards on the evacuees, mainly restricted to the effects of smoke density on evacuee's motion speed the and effects of smoke toxicity on their health conditions. Hypothesis II: since FREEgress considers relatively more comprehensive fire impacts compared to FDS+Evac, the simulation results reported by FREEgress would reflect more significant influence of fire hazards on evacuees' behaviors and the evacuation outcomes. To test the above hypotheses and verify FREEgress, a series of simulation experiments were conducted, as reported below.

4.2 Scenario descriptions and simulation settings

The indoor space of a museum [21] generated by AutoCAD [51] (version 2018) was used in the simulation. The floor plan of the museum is shown in Figure 6. In the simulation, the fire, set in Pyrosim (version 2017.1.0131), initially broke out at certain locations inside the museum, and then began to spread within the entire indoor space. The growth of fire was simulated using the T-square fire model [52], for which the heat release rate (HRR) was set to increase over time until it reached the maximum value that was set to be 8000 kW [53]. The spread of fire and smoke was simulated using FDS model (version 6.5.3) with Pyrosim (version 2017.1.0131). Fire data (temperature, heat flux, FED, FIC and extinction coefficient) were recorded at a one-second interval and transferred to FREEgress as explained in Section 4.3. In the simulation, a total of 48 occupants were modeled as intelligent agents in four exhibition areas, which represented a typical peak-hour density of visitors in museums [21]. These exhibition areas are illustrated with red boxes in Figure 7. The agents' initial locations were evenly distributed in these areas. The initial location of each agent within its designated area was randomly generated in the simulation.

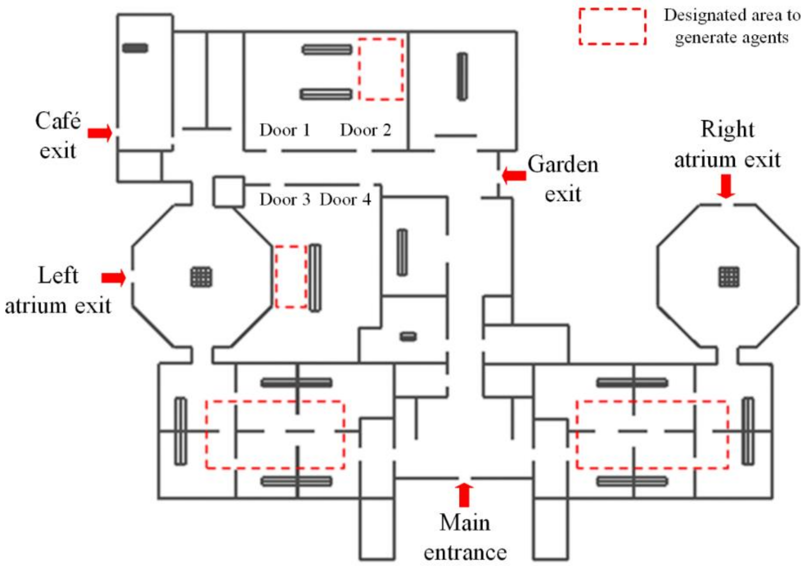


Figure 7: Floor plan of the museum and agents' initial locations for simulation

Three key factors were introduced in the simulations, the variations of which resulted in a number of different simulation scenarios. The first factor was initial fire location. The fire could break out near room entrances, blocking critical evacuation paths, or inside rooms, blocking non-evacuation critical paths, as illustrated in Figure 8. The second factor was delay time. Prior research pointed out that in many cases noticeable delay was observed between when the fire broke out and when evacuees began to escape [54, 55]. A longer delay time would mean that the evacuees would be faced with larger fire hazards duration evacuation. In the simulation, different delay time of evacuation (i.e., 0 second or 90 seconds) were set for all agents. The third factor was behavior type. Prior research pointed out that crowds had different behavioral patterns during fire evacuation [4]. Two behavior types were modeled in FREEgress, including perception-based behavior, which assumed that agents' navigation decision was dominated by their perception of the surrounding environment such as perception with navigation objects, and knowledge-based behavior, which assumed that agents' navigation decision was dominated by their prior knowledge about the space such as the familiarity with the location of exits.

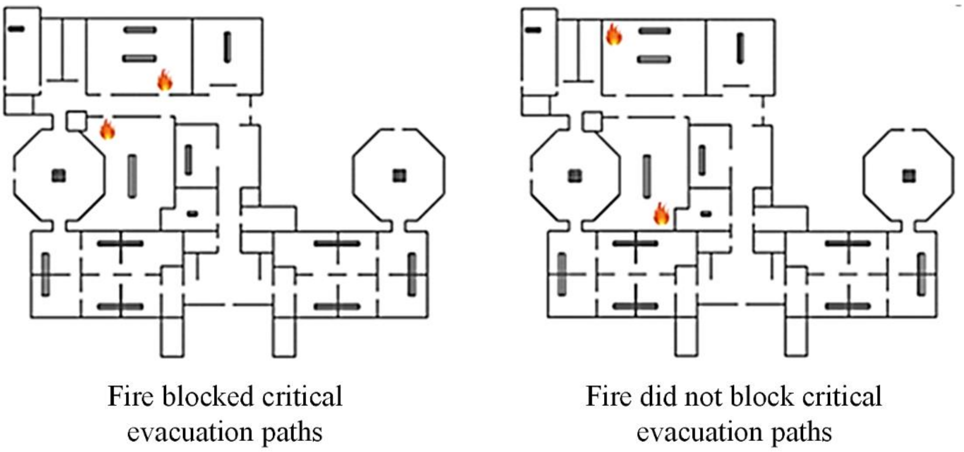


Figure 8: Two sets of fire locations

5. Model Verification Results

5.1 Comparison between FREEgress and SAFEgress

For comparison between FREEgress and SAFEgress, four scenarios were simulated in FREEgress enumerating all possible combinations of initial fire location and behavior type, and two scenarios were simulated in SAFEgress enumerating all possible values of behavior type. Delay time was set to be zero in all scenarios, thus in FREEgress the agents began to escape as soon as the fire broke out, so as to be consistent with the settings in SAFEgress. These scenarios are numbered from 1 to 6, and their settings are summarized in Table 2. Each scenario was simulated 10 times, and the convergence of the results from these simulations was checked. In terms of the median and average evacuation times, the ratio of standard deviation value to the average value did not exceed 8.0% for all scenarios, indicating notable convergence of the simulation results. The results were then averaged to avoid possible impact of randomness of agents' initial locations on the simulation results.

FREEgress-based and SAFEgress-based simulation results were compared, in terms of maximum, median and average evacuation times, as well as speed, route availability, number of fatalities, evacuation process and trajectory, which are key behavioral components for the verification of evacuation models [56]. The route availability referred to the routes available to evacuees [56]. It was represented by the accessibility of doors 1-4 (Figure 7) in this study. A door could become inaccessible owing to smoke, heat and high temperature in its surroundings. The evacuation process was depicted by the number of agents navigating to exits, which was changing dynamically over time from when the fire broke out to when all agents reached the exits or lost escape capability. Three scenarios (1, 2 and 5) assumed evacuee agents followed their knowledge to evacuate. As the simulation results failed the normality test, the Kruskal-Wallis H test was conducted to compare the maximum, median and average evacuation times, average speed and the number of fatalities between these three scenarios, and Pearson's Chi-squared test was conducted to compare the route availability. The statistical analysis results, as summarized in Table 3, indicated that at the 95% significance level there was no significant difference between scenario 1, 2 and 5 in terms of maximum, median and average evacuation times, route availability and number of fatalities. The only exception was the average speed, which was found to be significantly different between the three scenarios. The statistical significance of this difference was mainly owing to the small standard deviation (0.01 m/s), while the magnitude of the difference was rather small and negligible (less than 1.5%).

In addition, one simulation was randomly selected for each scenario, and the results from these simulations are plotted in Figures 9 and 10 for further comparison. Figure 9 illustrates the evacuation process in the three simulations. The Euclidean relative difference (ERD), Euclidean projection coefficient (EPC) and Secant cosine (SC), three widely used metrics that represented the overall agreement between two curves [56, 57], were calculated to measure the agreement between each pair of curves in the figure. The ranges of ERD, EPC and SC are in [0, +∞), [0, +∞) and [-1, 1], respectively. Two curves could be considered identical if ERD = 0, EPC = 1 and SC = 1. The acceptance criteria that should be satisfied for considering two curves as comparable, as recommend in prior research [57], are: ERD ≤ 0.45, 0.6 ≤ EPC ≤ 1.4 and, SC ≥ 0.6, with s/n ≤ 0.05, where s represents the period of noise in the data and n is the number of occupants. As it was necessary to keep the ratio s/n as low as possible [57], the value of s was chosen to be 1. In Figure 9, the maximum ERD value and the minimum EPC and SC values between any two curves were 0.13, 0.93 and, 0.63 (s = 1, n = 48, s/n = 0.02), respectively, which satisfied the acceptance criteria, indicating that the trend of the evacuation processes was generally consistent between scenarios 1, 2 and 5. Figure 10 shows the trajectories of all agents in the three simulations, which also indicated high consistency between the three different scenarios. It needs to be noted that the initial positions of the agents were randomly generated within the designated areas and hence not exactly the same for each simulation. Since multiple simulations were run for each simulation, the impact of randomness of the initial agent positions could be avoided.

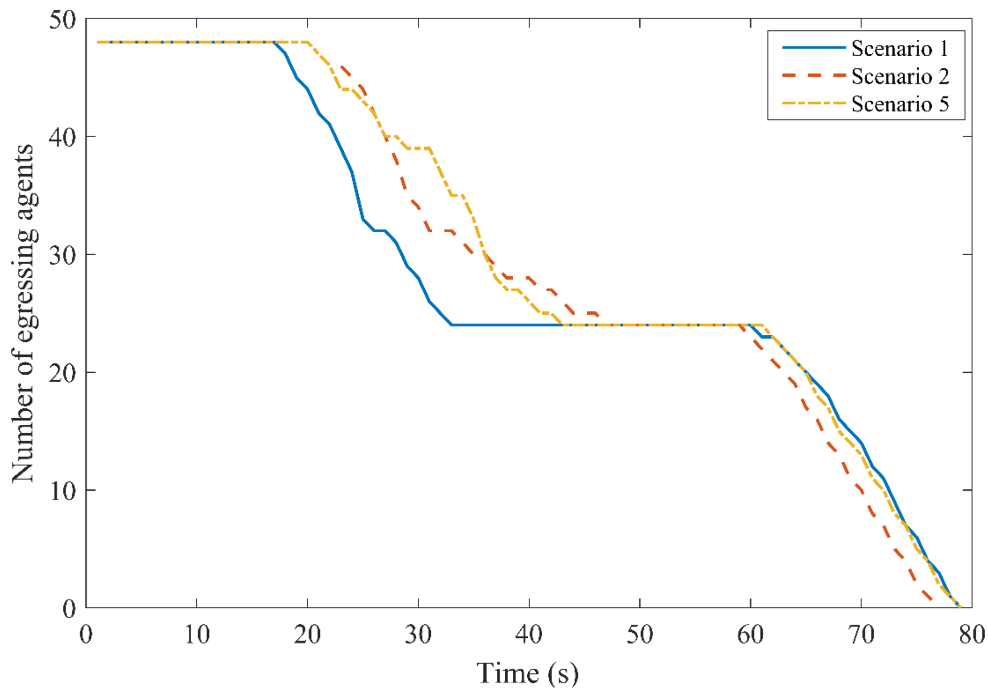
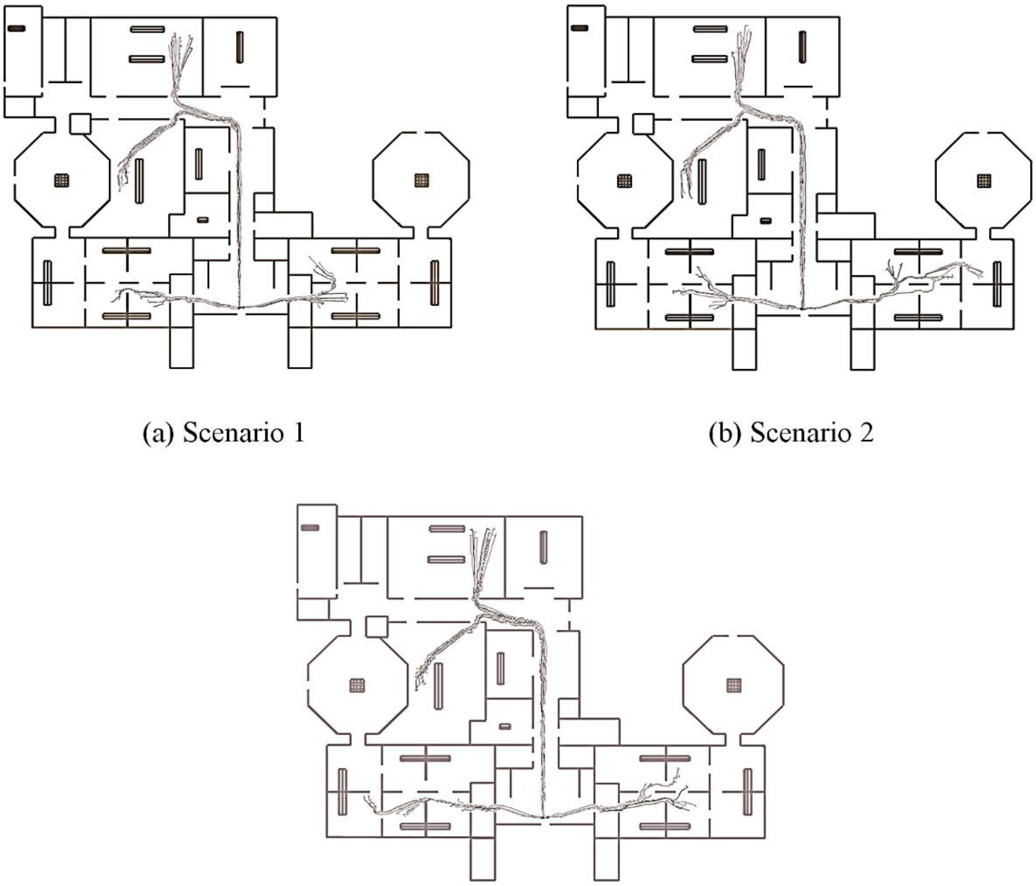


Figure 9: Evacuation processes in scenarios 1, 2 and 5



(a) Scenario 1 (b) Scenario 2

(c) Scenario 5

Figure 10: Egress trajectories of agents in scenraios 1, 2 and 5

Similarly, the results from scenarios 3, 4 and 6, which all assumed that evacuees only relied on their perception of the surrounding environment when making navigation decisions, were compared. As the simulation results failed the normality test, the Kruskal-Wallis H test was conducted to compare the maximum, median and average evacuation times, average speed and the number of fatalities between these three scenarios, and Pearson's Chi-squared test was conducted to compare the route availability. The statistical analysis results are summarized in Table 4. The evacuation times shown in the table were calculated after excluding agents that failed to escape, as these agents got lost at the emergency scenes and spent prolonged time that was very different than that of successfully escaped agents. The results indicated that at the 95% significance level there was no significant difference between scenarios 3, 4 and 6 in terms of maximum, median and average evacuation times, route availability and number of fatalities. The only exception was the average speed, which was found to be significantly different between the three scenarios. The statistical significance of this difference was mainly owing to the small standard deviation (0.01 m/s), while the magnitude of the difference was rather small and negligible (less than 1.5%). It needs to be noted that, in a few FREEgress-based simulations, one agent (2.1% of all agents) spent prolonged time looking for exits and taking detours, and eventually was not able to egress the museum. The above results indicated that, when only agents that successfully evacuated were counted, all performance indices were highly consistent between the three scenarios. It also needs to be noted that the initial positions of the agents were randomly generated within the designated areas and hence not exactly the same for each simulation. Since multiple simulations were run for each simulation, the impact of randomness of the initial agent positions could be avoided. Figure 11 illustrates the evacuation process in the three simulations. As shown in Figure 11, the maximum ERD value and minimum EPC and SC values between any two curves were 0.13, 0.96 and 0.65 ($s = 1$, $n = 48$, $s/n = 0.02$), respectively, which satisfied the acceptance criteria, indicating that the trend of the evacuation processes was generally consistent between scenarios 3, 4 and 6, despite that one agent (2.1% of all agents) in scenarios 3 and 4 spent prolonged time looking for exits and taking detours and eventually was not able to egress the museum, while all agents successfully evacuated in scenario 6. This demonstrated that the whole evacuation process existed reasonable differences between scenarios 3, 4 and 6.

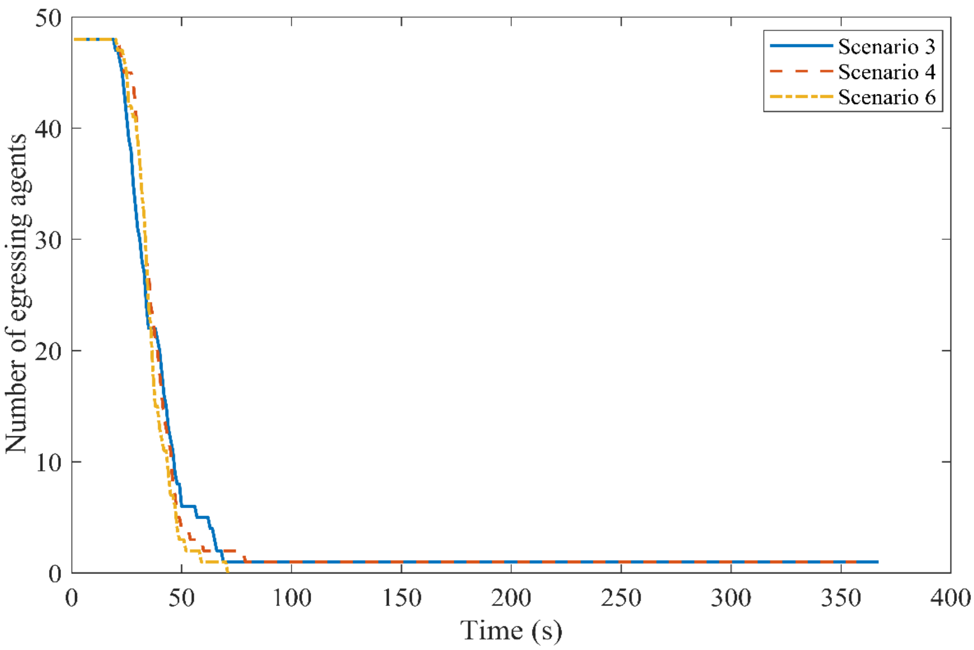


Figure 11: Evacuation processes in scenarios 3, 4 and 6

In conclusion, the above results showed that the simulation results of FREEgress and SAFEgress were consistent when the scale of fire was small, which supported Hypothesis I and suggested that FREEgress had appropriately inherited the efficacy of SAFEgress.

5.2 Comparison between FREEgress and FDS+Evac

For comparison between FREEgress and FDS+Evac, two scenarios were simulated in FREEgress and FDS+Evac enumerating all combinations of initial fire locations. Delay time was set to be 90 seconds in all scenarios to model the situation that the fire had significantly grown and spread when evacuees began to evacuate. To make the simulations comparable, agents in FREEgress and FDS+Evac were assigned with the same physical profile, such as body size, gender and movement speed [34], as summarized in Table 5. In addition, in FDS+Evac each agent was assigned to evacuate from a specific exit, whilst in FREEgress each agent was configured to adopt the knowledge-based behavior, which made the agent to also evacuate from a specific exit. It also needed to be noted that the average speed was not reported as an evacuation outcome in FDS+Evac. These scenarios are numbered from 7 to 10, and their settings are summarized in Table 6. Each scenario was simulated 10 times, and the convergence of the results from these simulations was checked. In terms of the median and average evacuation times, the ratio of standard deviation value to the average value did not exceed 3.2% for all scenarios, indicating notable convergence of the simulation results. The results were then averaged to avoid possible impact of randomness of agents' initial locations on the simulation results.

FREEgress-based and FDS+Evac-based simulation results were compared, in terms of total evacuation time, speed, route availability, number of fatalities, evacuation process and trajectory. Taking two scenarios (7 and 9), both of which assumed that the fire blocked critical evacuation paths and the delay time was 90 seconds, as an example. As the simulation results failed the normality test, the Mann-Whitney U test was conducted to compare the maximum, median and average evacuation times, average speed and the number of fatalities between these two scenarios, and Pearson's Chi-squared test was conducted to compare the route availability. The statistical analysis results summarized in Table 6 indicated that at the 95% significance level scenarios 7 and 9 were significantly different in terms of maximum, median and average evacuation times and route availability. The main reason was that FDS+Evac only considered the effects of smoke density on evacuees' motion speed and smoke toxicity on evacuees' health conditions, whereas FREEgress also considered various other impacts of fire on health, such as heat radiation and heat convection. Therefore, the motion speed of agents in FREEgress was slower than that in FDS+Evac under the same smoke density, and thus the evacuation time in FREEgress was longer than that in FDS+Evac. With respect to the difference in route availability, it was caused by the fact that, unlike FREEgress, FDS+Evac did not consider that flame and smoke could block certain routes and force evacuees to take detours. One simulation was randomly selected for each scenario, and the results from these simulations are plotted in Figures 12 and 13 for further comparison. In Figure 12, the ERD, EPC and SC values between the two curves were 0.21, 0.97 and 0.37 ($s = 1$, $n = 48$, $s/n = 0.02$), respectively, which did not satisfy the acceptance criteria, indicating that there was significant difference between the evacuation processes of scenarios 7 and 9. The agents' evacuation performance was generally consistent between the two scenarios before 150 seconds, after which some agents in scenario 7 had noticeably lower performance, mainly due to higher fire impacts imposed on them that led to slower motion speed. Figure 13 shows the trajectories of all agents in the two simulations. There was significant difference between the two plots, which was mainly caused by the fact that, unlike FREEgress, FDS+Evac did not consider that flame and smoke could block some routes and force evacuees to take detours when computing agents' evacuation routes. Such impacts could be significant when the fire was within critical evacuation routes (i.e., location I). It needs to be noted that the initial positions of the agents were randomly generated within the designated areas and hence not exactly the same for each simulation. Since multiple simulations were run for each simulation, the impact of randomness of the initial agent positions could be avoided. Lastly, similar findings were obtained from comparisons between scenarios 8 and 10. For the sake of brevity, the simulation results from scenarios 8 and 10 are not analyzed and discussed in detail. All results from these two scenarios can be found in the supplemental materials (Tables S1-S2 and Figures S1-S2) of this paper.

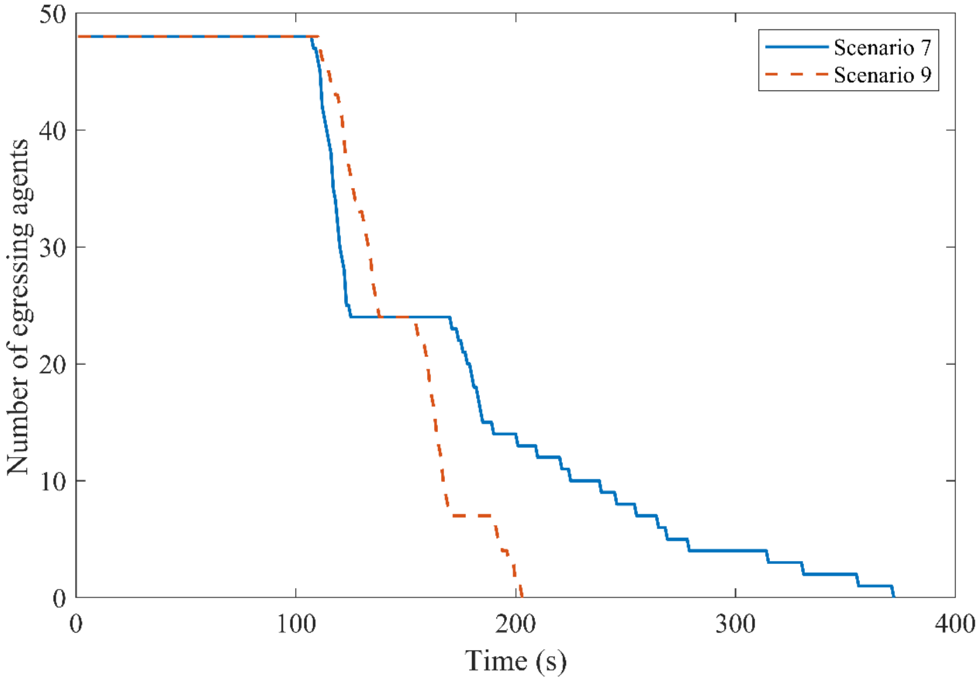
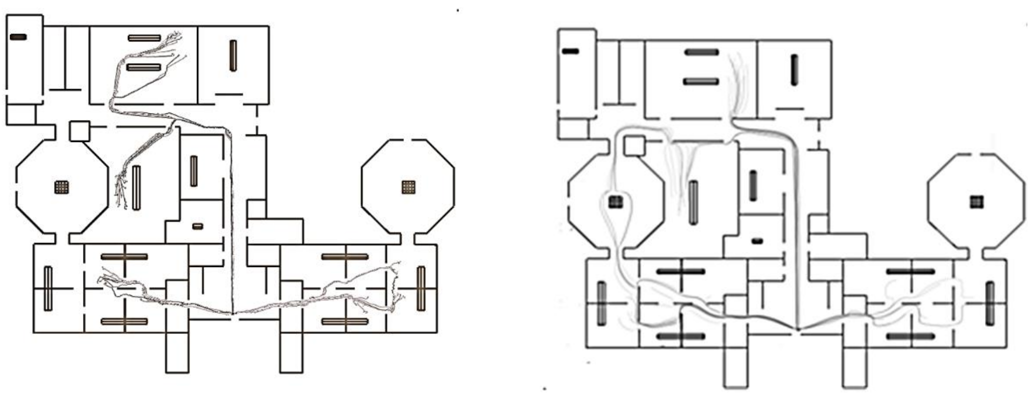


Figure 12: Evacuation processes in scenarios 7 and 9



(a) Scenario 7 (b) Scenario 9

Figure 13: Egress trajectories of agents in scenraios 7 and 9

In conclusion, the above results show that the FREEgress had generally comparable simulation performance to FDS+Evac, both of which incorporated smoke density and smoke toxicity impacts on evacuees' physiological conditions. The results also showed that FREEgress was more advantageous in that it also accounted for the physiological impacts of heat, and the impact of fire hazards on evacuee's route selection strategies and motion speed, which supported Hypothesis II. As a result, FREEgress was able to avoid underestimating the fire impacts on crowd evacuation.

Table 2: Settings for simulation scenarios 1-6

Simulator	Simulation scenario	Initial fire location (blocking critical evacuation paths?)	Delay time (s)	Behavior type
FREEgress	1	Yes	0	Knowledge-based
	2	No	0	Knowledge-based
	3	Yes	0	Perception-based
	4	No	0	Perception-based
SAFEgress	5	—	0	Knowledge-based
	6	—	0	Perception-based

Table 3: Comparison of simulation results from scenarios 1, 2 and 5

Simulator	Simulation scenario	Evacuation time (s)			Average speed (m/s)	Route availability	Number of fatalities
		Maximum	Median	Average			
FREEgress	1	77.6±1.5	50.5±2.5	50.4±1.5	1.30±0.01	Door 2&4	0.0±0.0
	2	76.3±0.7	50.3±2.1	49.4±0.99	1.32±0.01	Door 2&4	0.0±0.0
SAFEgress	5	76.5±1.3	49.5±2.1	49.3±1.2	1.32±0.01	Door 2&4	0.0±0.0
P-value		0.068	0.736	0.164	0.017	1.000	1.000

Note: The values in the table are based on the results of 10 simulations. The Kruskal-Wallis H test was conducted to analyze the results of maximum, median and average evacuation times, average speed and number of fatalities. Pearson's Chi-squared test was conducted to analyze the results of route availability.

Table 4: Comparison of simulation results from scenarios 3, 4 and 6

Simulator	Simulation scenario	Evacuation time (s)			Average speed (m/s)	Route availability	Number of fatalities
		Maximum	Median	Average			
FREEgress	3	77.0±12.0	35.3±2.8	38.8±2.3	1.33±0.01	Door 1-4	0.4±0.5
	4	72.5±11.0	35.0±2.0	36.7±1.8	1.35±0.01	Door 1-4	0.2±0.4

SAFEgress	6	69.3±17.6	34.0±2.3	36.0±1.7	1.34±0.01	Door 1-4	0.0±0.0
P-value		0.179	0.384	0.063	0.011	1.000	0.089

Note: The values in the table are based on the results of 10 simulations. The Kruskal-Wallis H test was conducted to analyze the results of maximum, median and average evacuation times, average speed and number of fatalities. Pearson's Chi-squared test was conducted to analyze the results of route availability.

Table 5: Agents' physical profiles in both FREEgress and FDS+Evac

Population type	Radius of whole body circle (m)	Radius of torso circle (m)	Radius of shoulder circle (m)	Movement speed (m/s)
Adult male	0.27	0.16	0.10	1.35

Table 6: Settings for simulation scenarios in 7-10

Simulator	Simulation scenario	Initial fire location (blocking critical evacuation paths?)	Delay time (s)	Behavior type
FREEgress	7	Yes	90	Knowledge-based
	8	No	90	Knowledge-based
FDS+Evac	9	Yes	90	-
	10	No	90	-

Table 7: Comparison of simulation results from scenarios 7 and 9

Simulator	Simulation scenario	Evacuation time (s)			Average speed (m/s)	Route availability	Number of fatalities
		Maximum	Median	Average			
FREEgress	7	369.8±38.2	148.0±2.0	176.7±4.5	1.11±0.01	Door 1&4	0.0±0.0
FDS+Evac	9	206±2.1	144.9±1.6	150.1±1.0	-	Door 2-4	0.0±0.0
P-value		< 0.001	0.003	< 0.001	-	0.040	1.000

Note: The values in the table are based on the results of 10 simulations. The Mann-Whitney U test was conducted to analyze the results of maximum, median and average evacuation times, average speed and number of fatalities. Pearson's Chi-squared test was conducted to analyze the results of route availability.

6. Case Study

In this section, FREEgress was used in a case study to conduct a series of simulations and to investigate how the aforementioned three factors, namely initial fire location, delay time and behavior type, might affect crowd evacuation in building fire emergencies. The goal of this case study was to demonstrate the functionality of FREEgress and its potential value in simulating various building evacuation scenarios and supporting subsequent analyses.

All simulations in the case study used the same environmental and agent settings as those in the model verification. A total of 30 scenarios were simulated. These scenarios enumerated all possible combinations of initial fire location (where fire blocked critical evacuation paths or not), delay time (0 s, 30 s, 60 s, 90 s, or 120 s) and behavior type (perception-based behavior, knowledge-based behavior, or following-leader behavior). The following-leader behavior assumed that an agent's navigation decision was impacted by a group leader, who was familiar with the surrounding environment and adopted knowledge-based behavior, and the crowd followed the group leader to evacuate [15]. The naming convention of $L_{c/nc}T_{0/30/60/90/120}B_{p/k/f}$ was applied to all scenarios to clearly demonstrate their settings. Specifically, the characters L, T and B referred to initial fire location, delay time and evacuee behavior, respectively, and their subscripts indicated the specific settings in a scenario. For example, scenario $L_cT_0B_p$ referred to a scenario where the fire blocked critical evacuation paths, the delay time was zero, and the agents adopted the perception-based behavior; Likewise, scenario $L_{nc}T_{30}B_k$ referred to a scenario where the fire did not block critical evacuation paths, the delay time was 30 seconds, and the agents adopted the knowledge-based behavior. All findings of the case study are reported and discussed as follows.

6.1 The impact of initial fire location

Based on analysis of the simulation results, the impacts of the initial fire location on maximum evacuation time, trajectory and health conditions were dependent on the settings of the scenarios. Specifically：

1) When the delay time $\leq$ 30 s and the agents adopted knowledge-based behavior or following-leader behavior, the initial fire location barely affected the evacuation outcomes. Taking the comparison between scenarios $\mathrm{L_c T_0 B_k}$ and $\mathrm{L_{nc} T_0 B_k}$ as an example. In both these scenarios, the delay time was zero, and the agents adopted the knowledge-based behavior. The fire blocked critical evacuation paths in scenario $\mathrm{L_c T_0 B_k}$ and did not in scenario $\mathrm{L_{nc} T_0 B_k}$. The simulation results, as summarized in Table 8, showed that the difference for the agents' maximum evacuation time in the two scenarios were within 3.8% and all agents successfully evacuated. As shown in Figure 14, the ERD, EPC and SC values between scenarios $\mathrm{L_c T_0 B_k}$ and $\mathrm{L_{nc} T_0 B_k}$ were 0.09, 1.01 and 0.75 (s = 1, n = 48, s/n = 0.02), respectively, which satisfied the acceptance criteria, indicating the evacuation processes were generally consistent between these two scenarios. The above results suggested that different initial fire locations had little impact on the agents' evacuation performance. This was further supported by Figures 15-16, which show that the agents' trajectories and the health condition of the agents were highly comparable between these two scenarios. Similar conclusions could also be derived from comparisons between scenarios $\mathrm{L_c T_{30} B_k}$ vs. $\mathrm{L_{nc} T_{30} B_k}$, $\mathrm{L_c T_0 B_f}$ vs. $\mathrm{L_{nc} T_0 B_f}$ and $\mathrm{L_c T_{30} B_f}$ vs. $\mathrm{L_{nc} T_{30} B_f}$. For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.

Table 8: Comparisoin of simulation results from scenarios $\mathrm{L_c T_0 B_k}$ and $\mathrm{L_{nc} T_0 B_k}$

Simulation scenario	Initial fire location (blocking critical evacuation paths?)	Maximum evacuation time (s)	Number of fatalities
$\mathrm{L_c T_0 B_k}$	Yes	76	0
$\mathrm{L_{nc} T_0 B_k}$	No	79	0

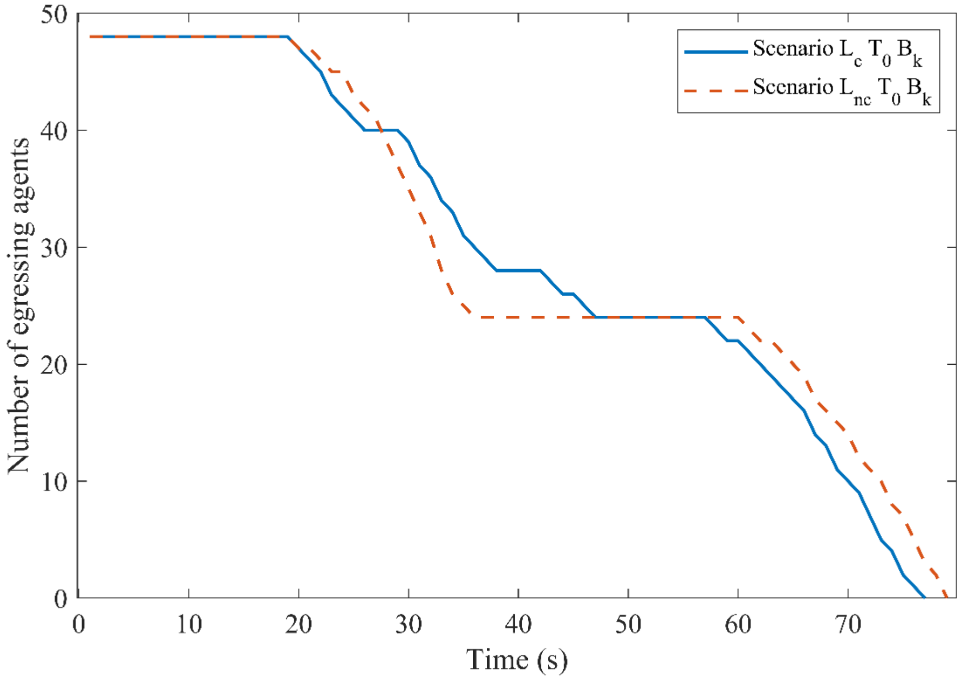
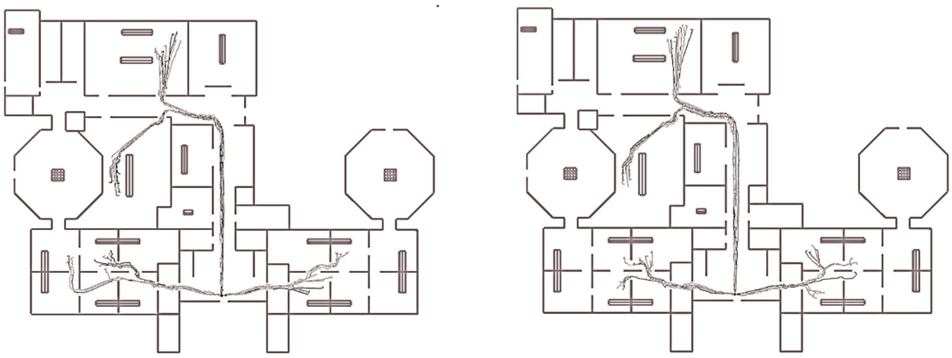


Figure 14: Evacuation processes in scenarios $L_cT_0B_k$ and $L_{nc}T_0B_k$



(a) Scenario $L_cT_0B_k$ (b) Scenario $L_{nc}T_0B_k$

Figure 15: Egress trajectories of agents in scenarios $L_cT_0B_k$ and $L_{nc}T_0B_k$

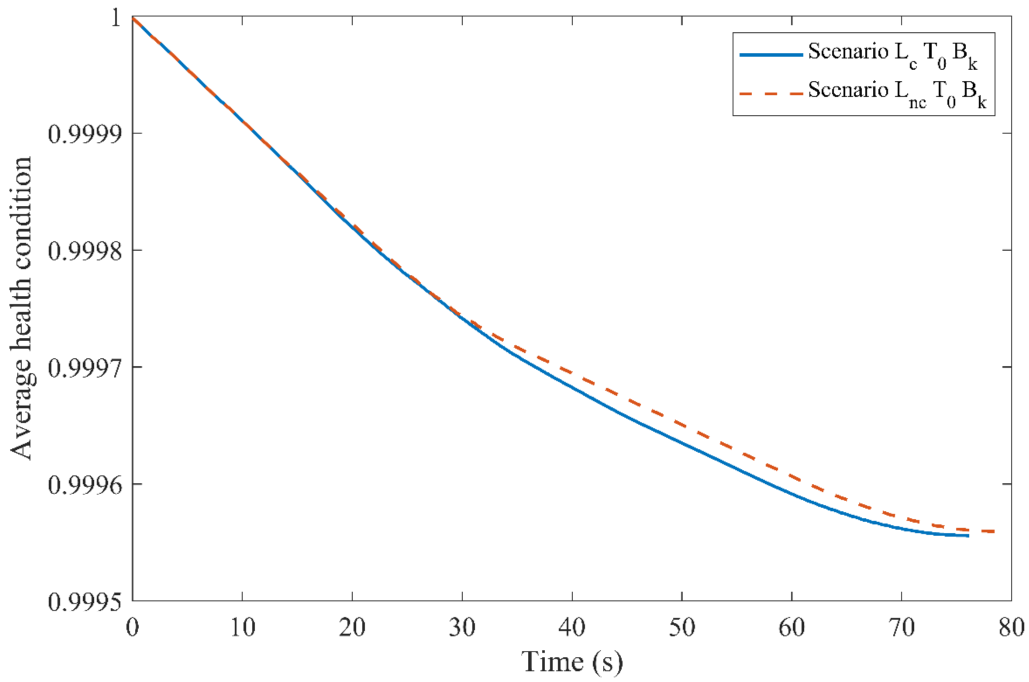
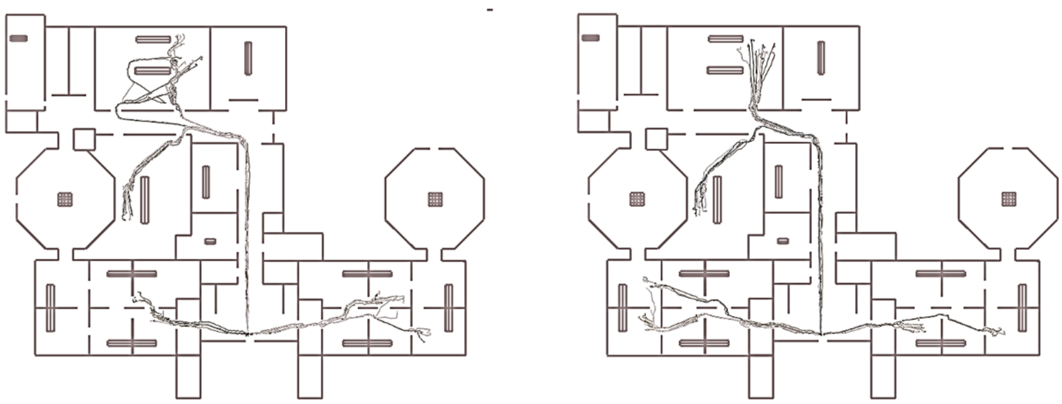


Figure 16: Average health condition of agents in scenarios $L_cT_0B_k$ and $L_{nc}T_0B_k$

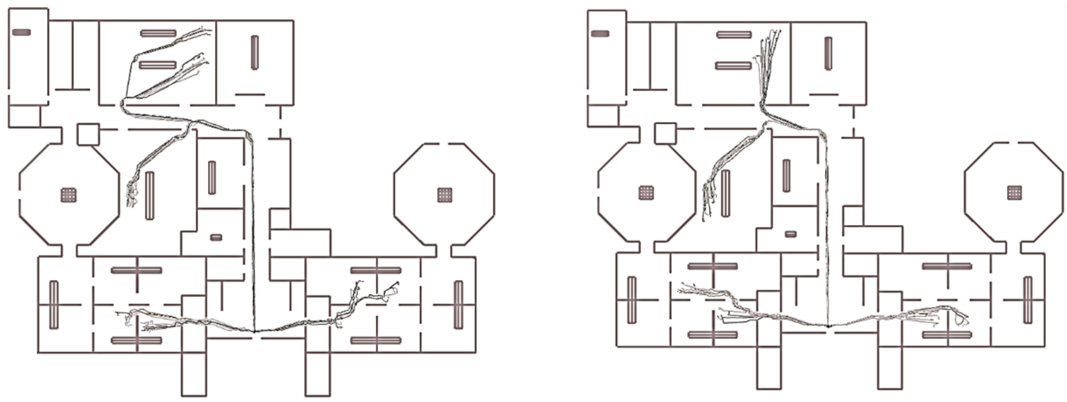
2) When the delay time > 30 s and regardless of the behavior type, fire that blocked critical evacuation paths caused agents to take detours. This trend became more remarkable as the delay time increased. Taking the comparison between scenarios $L_cT_{60}B_k$ and $L_{nc}T_{60}B_k$ as an example. In both these scenarios, the delay time was 60 seconds, and the agents adopted the knowledge-based behavior. The fire blocked critical evacuation paths in scenario $L_cT_{60}B_k$ and did not in scenario $L_{nc}T_{60}B_k$. A large portion of the agents in scenario $L_cT_{60}B_k$ changed their direction and chose the door far away from the initial fire location to evacuate, which led to detoured trajectories that were different from the trajectories in scenario $L_{nc}T_{60}B_k$. When the delay time increased to 90 seconds, the difference between trajectories from scenario $L_cT_{90}B_k$ and those from scenario $L_{nc}T_{90}B_k$ became more significant. The simulation results are also illustrated in Figures 17-18. The results suggested that when fire blocked critical evacuation paths, agents would need to take detours to avoid the fire, and their trajectories as well as evacuation performance would be significantly impacted. Similar conclusions could also be derived from comparisons between scenarios $L_cT_{120}B_k$ vs. $L_{nc}T_{120}B_k$ (enumeration over behavior types and values of delay time for 60 s, 90 s and 120 s). For the sake of brevity, the simulation results from these comparisons are not analyzed

and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.



(a) Scenario $L_cT_{60}B_k$ (b) Scenario $L_{nc}T_{60}B_k$

Figure 17: Egress trajectories of agents in scenarios $L_cT_{60}B_k$ and $L_{nc}T_{60}B_k$



(a) Scenario $L_cT_{90}B_k$ (b) Scenario $L_{nc}T_{90}B_k$

Figure 18: Egress trajectories of agents in scenarios $L_cT_{90}B_k$ and $L_{nc}T_{90}B_k$

3) When the delay time > 30 s, fire that blocked critical evacuation paths exposed agents to noticeable risks, as reflected by their health conditions. Taking the comparison between scenarios $L_cT_{60}B_p$ and $L_{nc}T_{60}B_p$ as an example. In both scenarios, the delay time was 60 seconds, and the agents adopted the perception-based behavior. The fire blocked critical evacuation paths in scenario $L_cT_{60}B_p$ and did not in scenario $L_{nc}T_{60}B_p$. The health conditions of the agents in scenario $L_cT_{60}B_p$ were remarkably lower than those in scenario $L_{nc}T_{60}B_p$. The simulation results are also illustrated in Figure 19. In addition, as shown in Table 9, compared to scenario $L_{nc}T_{60}B_p$, fatalities were much higher in scenario $L_cT_{60}B_p$.

This was mainly because more agents lost escape capability at an earlier stage and the evacuation process was forced to end sooner in scenario $L_cT_{60}B_p$. This suggested that different initial fire locations would expose the agents to different levels of risk, imposing significant impact on the evacuation outcomes. Similar conclusions could also be derived from comparisons between scenarios $L_cT_{90}B_p$ vs. $L_{nc}T_{90}B_p$ (enumeration over behavior types and values of delay time for 60 s, 90 s and 120 s). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.

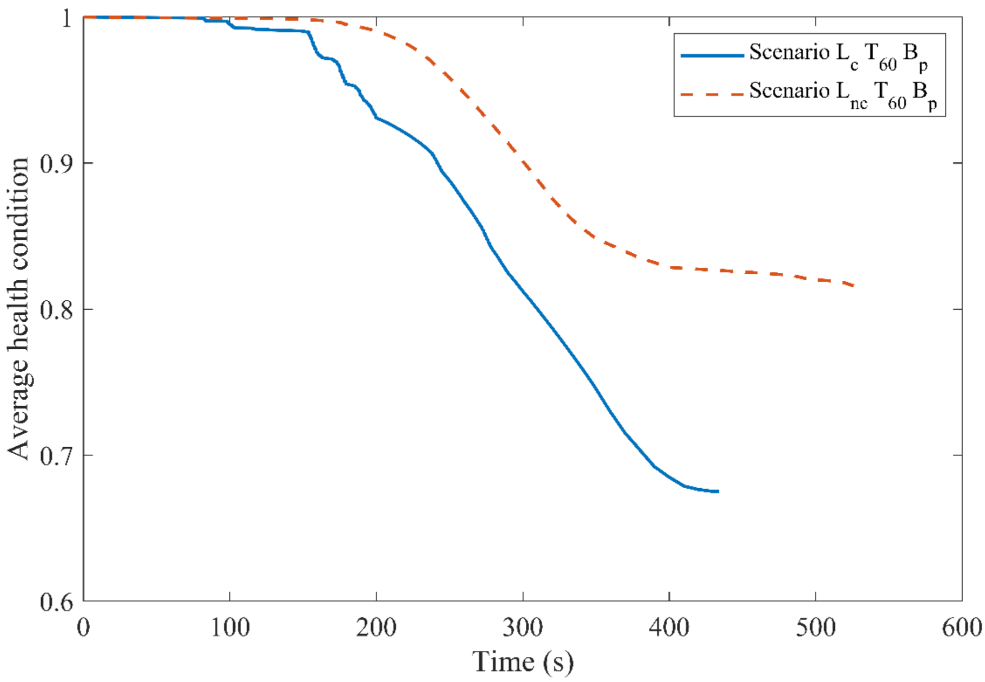


Figure 19: Average health condition of agents in scenarios $L_cT_{60}B_p$ and $L_{nc}T_{60}B_p$

Table 9: Comparisoin of simulation results from scenarios $L_cT_{60}B_p$ and $L_{nc}T_{60}B_p$

Simulation scenario	Initial fire location (blocking critical evacuation paths?)	Maximum evacuation time (s)	Number of fatalities
$L_cT_{60}B_p$	Yes	434	17
$L_{nc}T_{60}B_p$	No	532	10

6.2 The impact of delay time

Based on analysis of the simulation results, the impacts of delay time on maximum and net evacuation time, trajectory and health conditions were dependent on the settings of the scenarios. Specifically:

1) When the delay time $\geq$ 30 s and the agents adopted knowledge-based or following-leader behavior, longer delay time generally correlated with longer maximum evacuation time and net evacuation time (maximum evacuation time minus delay time). Such impact grew disproportionally fast as the delay time increased. Taking the comparison from scenarios $\mathrm{L_cT_0B_k}$ to $\mathrm{L_cT_{120}B_k}$ (enumeration over values of delay time) as an example. In these scenarios, the fire blocked critical evacuation paths and the agents adopted the knowledge-based behavior. The simulation results, as summarized in Table 10, showed that the net evacuation time was nearly the same in scenarios $\mathrm{L_cT_0B_k}$ and $\mathrm{L_cT_{30}B_k}$. However, without counting the delay time, it took the agents 83 seconds (106%) longer to evacuate from the museum in scenario $\mathrm{L_cT_{60}B_k}$ compared to $\mathrm{L_cT_{30}B_k}$, while agents in scenario $\mathrm{L_cT_{90}B_k}$ needed 120 seconds (75%) longer to egress compared to $\mathrm{L_cT_{60}B_k}$. The net evacuation time increased by another 135 seconds (48%) in $\mathrm{L_cT_{120}B_k}$, compared to $\mathrm{L_cT_{90}B_k}$, when the delay time increased to 120 seconds. The above simulation results were plotted in Figure 20. The maximum ERD value and minimum EPC and SC values between any two curves were 0.83, 0.25 and 0.01 (s = 1, n = 48, s/n = 0.02), respectively, which did not satisfy the acceptance criteria, indicating that there was notable difference between the evacuation processes of these five scenarios. The results suggested that the time required for the agents to complete evacuation would be significantly prolonged when the delay time increased. Similar conclusions could also be derived from comparisons between scenarios $\mathrm{L_{nc}T_0B_k}$ to $\mathrm{L_{nc}T_{120}B_k}$, $\mathrm{L_cT_0B_f}$ to $\mathrm{L_cT_{120}B_f}$ and $\mathrm{L_{nc}T_0B_f}$ to $\mathrm{L_{nc}T_{120}B_f}$(enumeration over values of delay time). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.

Table 10: Comparisoin of simulation results from scenarios $L_cT_0B_k$ to $L_cT_{120}B_k$ (enumeration over values of delay time)

Simulation scenario	Delay time (s)	Maximum evacuation time (s)	Net evacuation time (s)	Number of fatalities
$L_cT_0B_k$	0	76	76	0
$L_cT_{30}B_k$	30	108	78	0
$L_cT_{60}B_k$	60	221	161	0
$L_cT_{90}B_k$	90	371	281	0
$L_cT_{120}B_k$	120	536	416	12

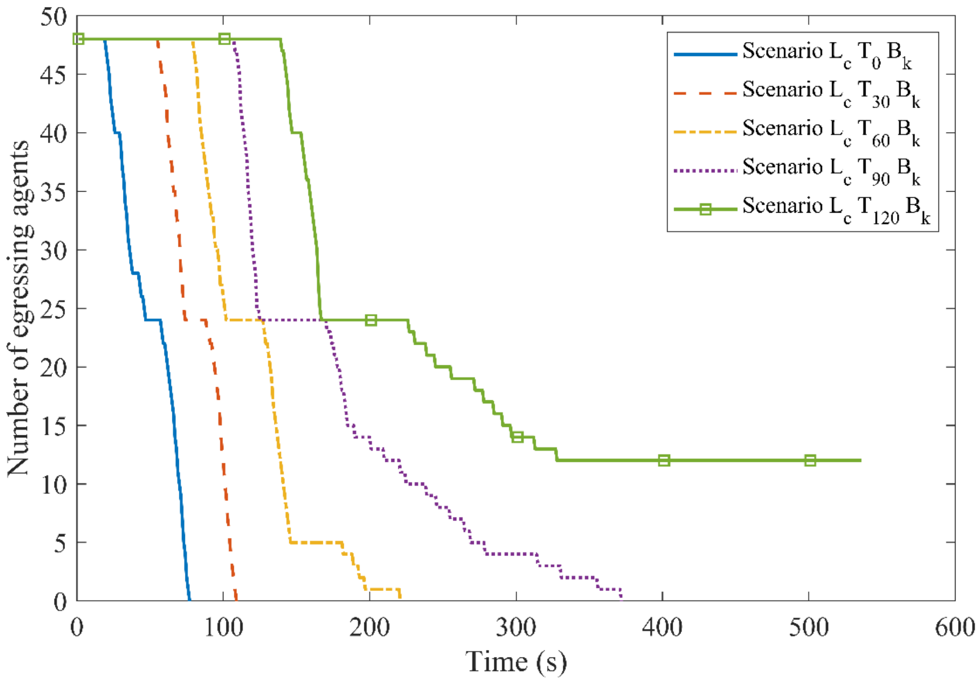
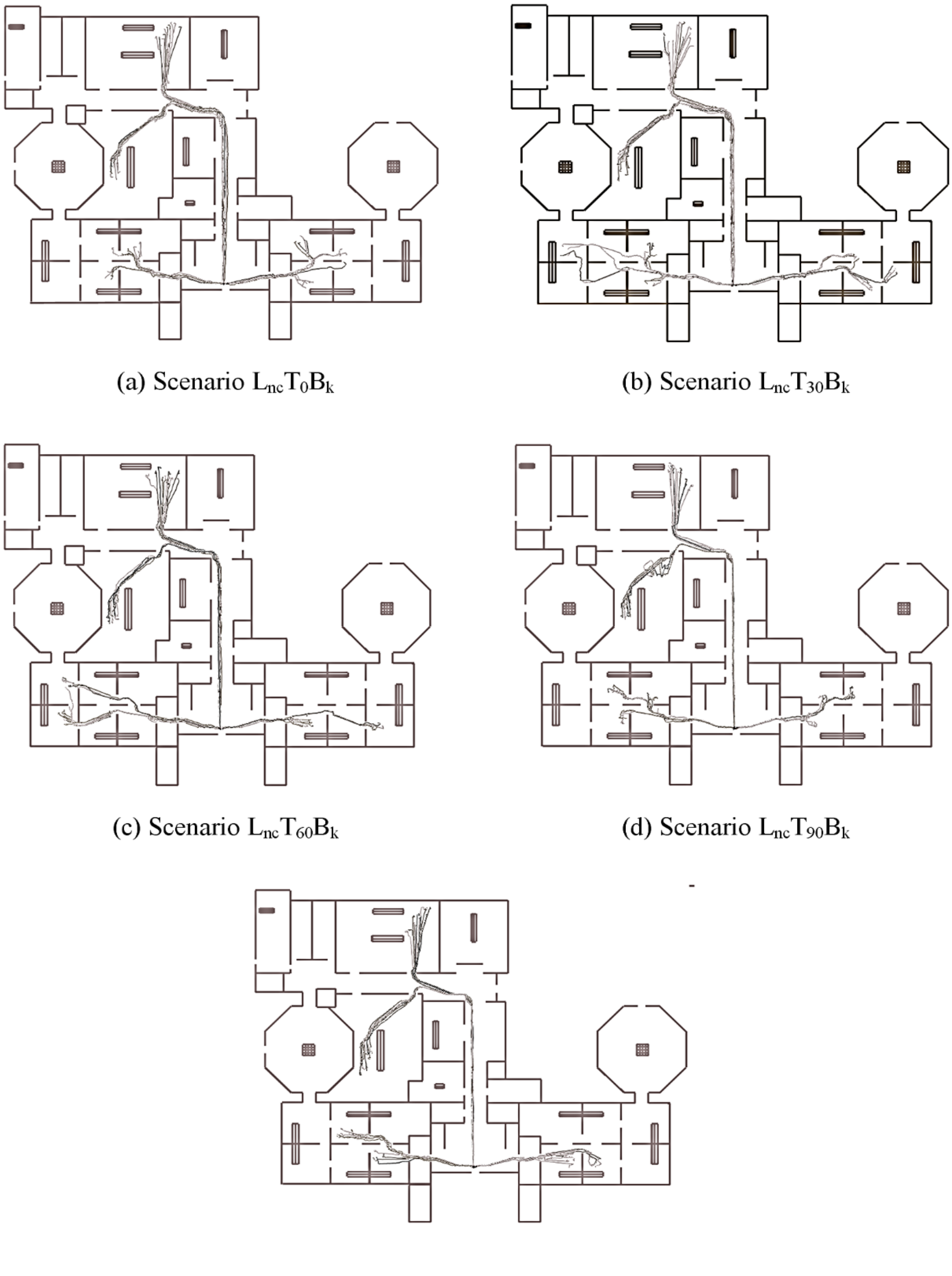


Figure 20: Evacuation processes in scenarios $L_cT_0B_k$ to $L_cT_{120}B_k$ (enumeration over values of delay time)

2) When the fire blocked non-critical evacuation paths, delay time barely impacted agents' evacuation route selection in scenarios. Taking the comparison between scenarios $L_{nc}T_0B_k$ to $L_{nc}T_{120}B_k$ (enumeration over values of delay time) as an example. In these scenarios, the fire did not block critical evacuation paths and the agents adopted the knowledge-based behavior. As the delay time increased from 0 to 120 seconds, agents showed highly consistent trajectories. The results are further illustrated in Figure 21. The results suggested that different delay time had limited impact on the agents' evacuation trajectories, as long as the critical evacuation paths were not blocked by fire. Similar conclusions could also be derived from

comparisons between scenarios $L_{nc}T_0B_p$ to $L_{nc}T_{120}B_p$ as well as $L_{nc}T_0B_f$ to $L_{nc}T_{120}B_f$ (enumeration over values of delay time). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.



(a) Scenario $L_{nc}T_0B_k$

(b) Scenario $L_{nc}T_{30}B_k$

(c) Scenario $L_{nc}T_{60}B_k$

(d) Scenario $L_{nc}T_{90}B_k$

(e) Scenario $L_{nc}T_{120}B_k$

Figure 21: Egress trajectories of agents in scenarios $L_{nc}T_0B_k$ to $L_{nc}T_{120}B_k$ (enumeration over values of delay time)

3) When the delay time $>$ 90 s, longer delay time exposed the agents to high risks. Taking the comparison from scenarios $L_cT_0B_k$ to $L_cT_{120}B_k$ (enumeration over values of delay time) as an example. In these scenarios, the fire blocked critical evacuation paths and the agents adopted the knowledge-based behavior. As the delay time increased from 0 to 90 seconds, the health conditions of agents were nearly consistent, and no fatalities occurred. However, as the delay time increased from 90 to 120 seconds, the health conditions of agents significantly decreased, and fatalities substantially increased. The simulation results are further illustrated in Figure 22 and shown in Table 10. The results suggested that longer delay time significantly lowered agents' health condition. Similar conclusions could also be derived from comparisons between scenarios $L_{nc}T_0B_k$ to $L_{nc}T_{120}B_k$, $L_cT_0B_p$ to $L_cT_{120}B_p$, $L_{nc}T_0B_p$ to $L_{nc}T_{120}B_p$, $L_cT_0B_f$ to $L_cT_{120}B_f$ and $L_{nc}T_0B_f$ to $L_{nc}T_{120}B_f$ (enumeration over values of delay time). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.

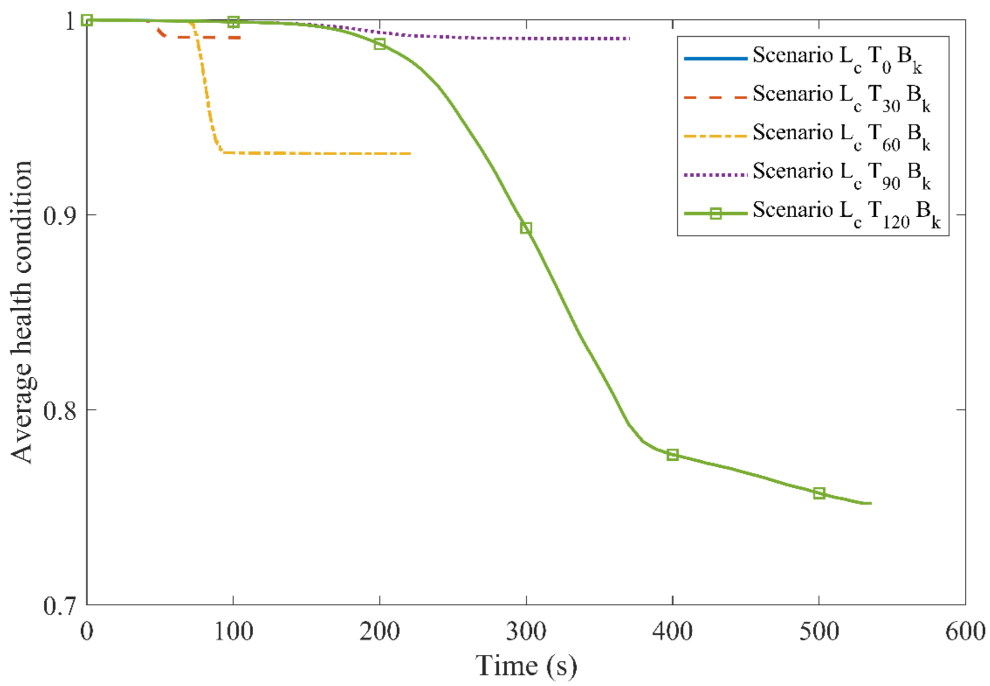


Figure 22: Average health condition of agents in scenarios $L_cT_0B_k$ to $L_cT_{120}B_k$ (enumeration over values of delay time)

6.3 The impact of behavior type

Based on analysis of the simulation results, the impacts of behavior type on maximum evacuation time, trajectory and health conditions were dependent on the settings of the scenarios. Specifically:

1) When the delay time $\geq$ 30 s, the knowledge-based evacuation strategy was the most efficient, followed by the following-leader strategy and then the perception-based strategy. Taking the comparison between scenarios $\mathrm{L_cT_{60}B_p}$, $\mathrm{L_cT_{60}B_k}$ and $\mathrm{L_cT_{60}B_f}$ as an example. In these scenarios, the delay time was 60 seconds and the fire blocked the critical evacuation paths. The agents adopted the perception-based behavior in scenario $\mathrm{L_cT_{60}B_p}$, knowledge-based behavior in scenario $\mathrm{L_cT_{60}B_k}$ and following-leader behavior in scenario $\mathrm{L_cT_{60}B_f}$. The simulation results, as summarized in Table 11, showed that fatalities in scenario $\mathrm{L_cT_{60}B_p}$ were significantly larger than those in scenario $\mathrm{L_cT_{60}B_k}$ and $\mathrm{L_cT_{60}B_f}$. Moreover, it took the agents in scenario $\mathrm{L_cT_{60}B_p}$ 213 seconds (49%) and 105 seconds (24%) longer to evacuate from the museum compared with scenario $\mathrm{L_cT_{60}B_k}$ and $\mathrm{L_cT_{60}B_f}$, respectively. The above simulation results are plotted in Figure 23. The maximum ERD value and minimum EPC and SC values between any two curves were 0.59, 0.95 and 0.22 ($s = 1$, $n = 48$, $s/n = 0.02$), respectively, which did not satisfy the acceptance criteria, indicating that notable differences existed between the evacuation processes of these three scenarios. The illustrations suggested that agents with the knowledge-based behavior and following-leader behavior were actually more efficient than agents with the perception-based behavior in finding and reaching the exits. Similar conclusions could also be derived from comparisons between scenarios $\mathrm{L_cT_{30}B_p}$ vs. $\mathrm{L_cT_{30}B_k}$ vs. $\mathrm{L_cT_{30}B_f}$ as well as $\mathrm{L_{nc}T_{30}B_p}$ vs. $\mathrm{L_{nc}T_{30}B_k}$ vs. $\mathrm{L_{nc}T_{30}B_f}$ (enumeration over values of delay time for 30 s, 60 s, 90 s and 120 s). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.

Table 11: Comparisoin of simulation results in scenarios $\mathrm{L_cT_{60}B_p}$, $\mathrm{L_cT_{60}B_k}$ and $\mathrm{L_cT_{60}B_f}$

Simulation scenario	Behavior pattern	Maximum evacuation time (s)	Number of fatalities
$\mathrm{L_cT_{60}B_p}$	Perception-based	434	17
$\mathrm{L_cT_{60}B_k}$	Knowledge-based	221	0

$L_cT_{60}B_f$	Following-leader	329	0

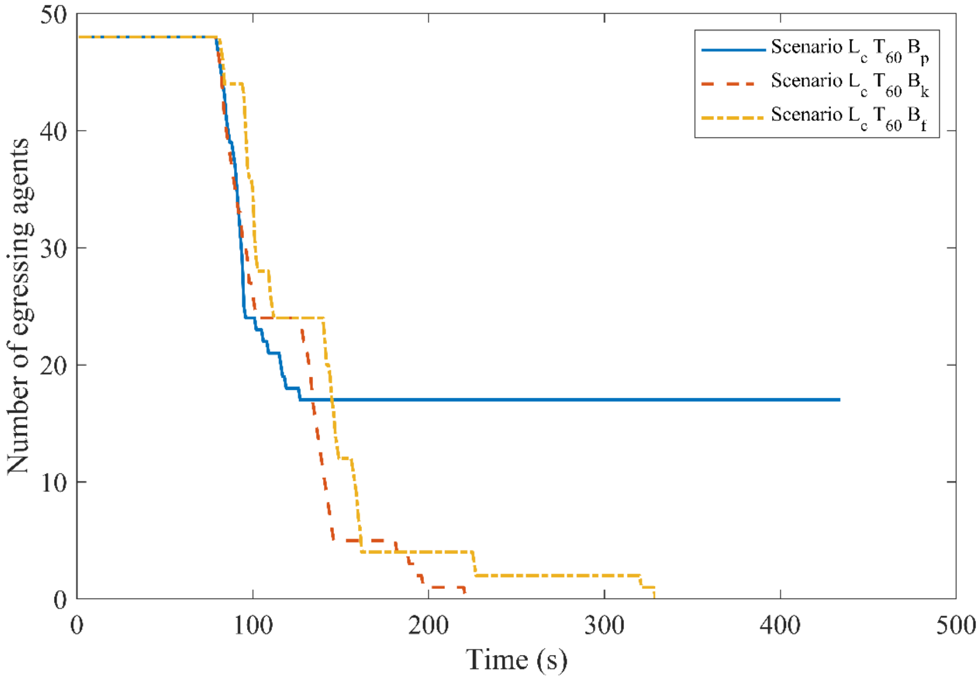
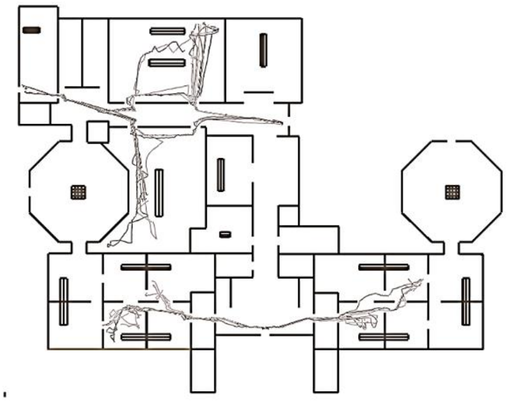
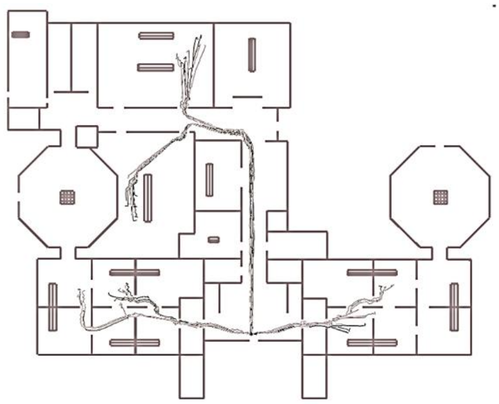


Figure 23: Evacuation processes in scenarios $L_cT_{60}B_p$, $L_cT_{60}B_k$ and $L_cT_{60}B_f$

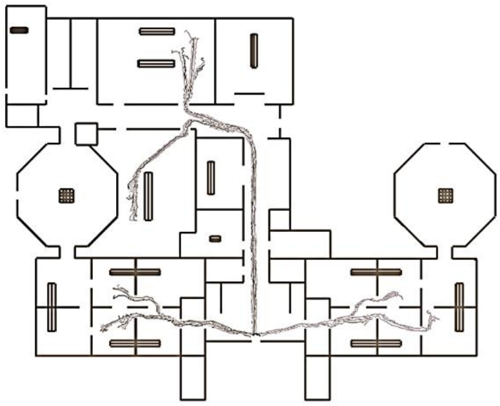
2) Agents with knowledge-based behavior and following-leader behavior exhibited consistent trajectories, which were different than those by agents with perception-based behavior. Taking the comparison between scenarios $L_cT_0B_p$, $L_cT_0B_k$ and $L_cT_0B_f$ as an example. In these scenarios, the delay time was zero second and the fire blocked critical evacuation paths. The agents adopted the perception-based behavior in scenario $L_cT_0B_p$, knowledge-based behavior in scenario $L_cT_0B_k$ and following-leader behavior in scenario $L_cT_0B_f$. The agents' trajectories in scenario $L_cT_0B_k$ were highly similar to those in scenario $L_cT_0B_f$, but distinct from those in scenario $L_cT_0B_p$. The simulation results are further illustrated in Figure 24. The results suggested that different behaviors significantly impacted agents' route selection. Similar conclusions could also be derived from comparisons between scenarios $L_cT_{30}B_p$ vs. $L_cT_{30}B_k$ vs. $L_cT_{30}B_f$ as well as $L_{nc}T_0B_p$ vs. $L_{nc}T_0B_k$ vs. $L_{nc}T_0B_f$ (enumeration over values of delay time). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.



(a) Scenario $L_cT_0B_p$



(b) Scenario $L_cT_0B_k$



(c) Scenario $L_cT_0B_f$

Figure 24: Egress trajectories of agents in scenarios $L_cT_0B_p$, $L_cT_0B_k$ and $L_cT_0B_f$

3) When the delay time $\geq$ 30 seconds, agents with perception-based behavior were exposed to the most health risks and agents with knowledge-based behavior were exposed to the least health risks. Taking the comparison between scenarios $L_cT_{90}B_p$, $L_cT_{90}B_k$ and $L_cT_{90}B_f$ as an example. In these scenarios, the delay time was 90 seconds and the fire blocked the critical evacuation paths. The agents adopted the perception-based behavior in scenario $L_cT_{90}B_p$, knowledge-based behavior in scenario $L_cT_{90}B_k$ and following-leader behavior in scenario $L_cT_{90}B_f$. Agents in scenario $L_cT_{90}B_k$ and scenario $L_cT_{90}B_f$ were fully or almost fully healthy when they reached the exits. However, the health conditions of agents in scenario $L_cT_{90}B_p$ were remarkably decreased during evacuation. The simulation results are further illustrated in Figure 25. The results suggested that agents with knowledge-based behavior and following-leader behavior were more capable of evacuating from the burning museum than agents with perception-based behavior. Similar conclusions could also be derived from comparisons

between scenarios $L_cT_{30}B_p$ vs. $L_cT_{30}B_k$ vs. $L_cT_{30}B_f$ as well as $L_{nc}T_{30}B_p$ vs. $L_{nc}T_{30}B_k$ vs. $L_{nc}T_{30}B_f$ (enumeration over values of delay time for 30 s, 60 s, 90 s and 120 s). For the sake of brevity, the simulation results from these comparisons are not analyzed and discussed in detail. All results of these scenarios can be found in the supplemental materials (Table S3) of this paper.

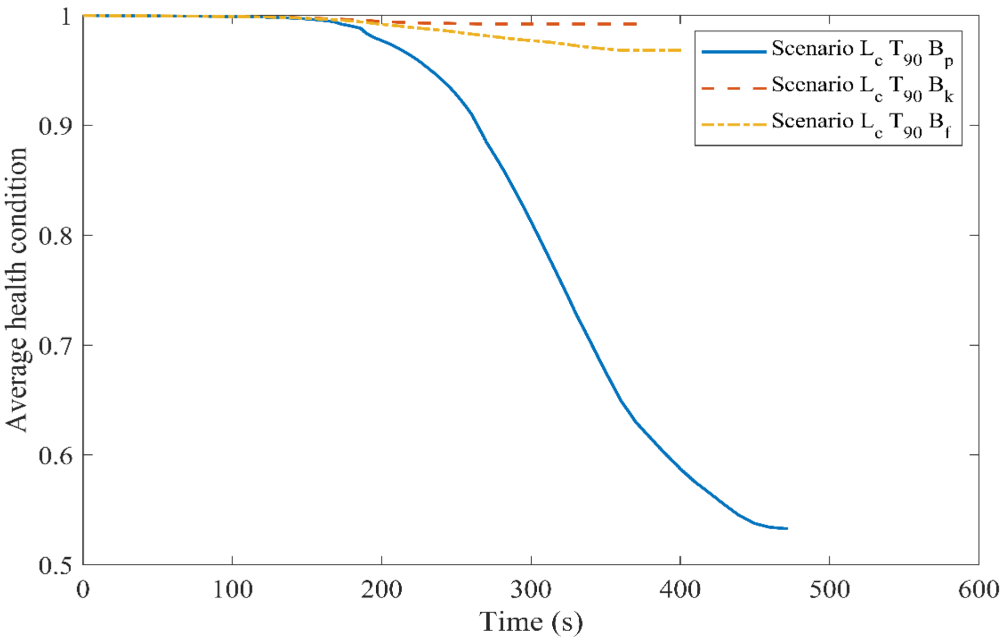


Figure 25: Average health condition of agents in scenarios $L_cT_{90}B_p$, $L_cT_{90}B_k$ and $L_cT_{90}B_f$

6.4 Discussions

To sum up, the main findings of the case study included that 1) when evacuation delay time was short, the initial fire location had little impact on the evacuation outcomes. When the delay time increases, the initial fire location started to impact the evacuation outcomes (such as prolonging evacuation and increasing fatalities); 2) Controlling for delay time, when the fire broke out on critical evacuation paths, the evacuation outcomes were worse (i.e., higher number of fatalities, more damaged health conditions and changing evacuation route selection) compared to cases where the fire broke out on non-critical evacuation paths; and 3) Controlling for delay time and fire pattern in the case study, the evacuation was the most efficient when the occupants adopted the knowledge-based behavior. The evacuation became less efficient when the occupants adopted the following-leader behavior, and was the least efficient when they adopted the perception-based behavior and made their navigation decisions based on visible building features (such as signs and doors).

It needs to be noted that the above findings are based on a particular spatial configuration in the case study and have not been generalized to all buildings. That being said, the methodology demonstrated in the case study to incorporate different factors and test their individual and collective effects can also be applied to other buildings using the functionalities of FREEgress, which provides the possibility of testing the same sets of factors in other buildings to assess the transferability of the reported findings in future research. In addition, future research can also include studies that assess the effects of the factors in standard tests, such as those developed by the International Maritime Organization (IMO) [58] or their modified versions developed for building contexts by the NIST [56], for further validation of FREEgress and improved transferability of the findings.

The proposed FREEgress model can be used to support both the safety design of new buildings and maintenance and emergency management of constructed facilities. Specifically, it can be used to assess the egress performance of new building designs in different fire scenarios, to evaluate evacuation training and procedures that directly influence the delay time and evacuation behaviors of building occupants, to assess the effectiveness of fire emergency management plans and to investigate the impacts of key factors on human evacuation efficiency so as to support fire emergency response decisions.

7. Conclusions and Future Research

A multiagent-based building fire evacuation simulation model, FREEgress, was developed in this study. By simulating the influences of heat, temperature, toxic gas and smoke particles on evacuees' mobility, navigation decision making and health conditions, FREEgress is capable of incorporating dynamic fire hazard impacts in the simulation of navigation of individual evacuees and the overall evacuation process. The efficacy of FREEgresss was verified by comparing its simulation results with those of SAFEgress and FDS+Evac. Furthermore, through using FREEgress, the impacts of three important factors, including initial fire location, evacuation delay time and evacuee behavior type, on the evacuation process and evacuation outcomes were examined in a case study, based on the simulation results in 30 different scenarios. The case study results showed that, by modeling the fire pattern and considering its dynamic physiological and psychological effects on simulated occupants, FREEgress is able to demonstrate the interaction effects of different variables that can critically determine the outcomes of evacuation.

Several efforts could be made in future research to improve FREEgress further to achieve more accurate, realistic and usable simulation of building fire evacuation. First, standard validation tests, such as those recommended by IMO [58] and NIST [56], can be applied to validate the proposed FREEgress model. Moreover, behavioral data with high validity (e.g., data from real fire events) when made available can also be used to validate FREEgress further. Second, more complex cognitive processes involved in human wayfinding behavior, especially those that may be evoked or impacted by emergency-induced mental pressure caused by fire emergencies, could be examined and incorporated in the simulation. Third, to better simulate individual behavioral uncertainty with respect to agents' response to the dynamic impacts of fire hazard, instead of using the current rule-based model, a fuzzy approach can be incorporated into the agent decision-making process in the future work. Fourth, evacuee behavior such as firefighting may impact the development of fire hazards, which would consequently impact the effects of fire hazards on evacuee behaviors. This closed loop of impact could be modeled to better reflect the dynamic nature of fire impacts on evacuation. Finally, better interfaces of FREEgress with building information modeling tools and fire dynamics simulation tools and better user interfaces could be developed to improve the level of data interoperability and user friendliness, enhancing its usability in real-world engineering applications.

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