Engineering Applications of Artificial Intelligence 127 (2024) 107401

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Agent-based modeling of high-rise building fires reveals self-rescue behaviors and better fire protection designs

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ARTICLE INFO

Keywords:
Crowd dynamics
High-rise building fires
Social force model
Self-rescue behaviors

ABSTRACT

It is always challenging to seek external rescue assistance in high-rise building fires. Therefore, it is critical for individuals to master survival skills. For crowd dynamics modeling, previous research focused on numerical simulations and building designs with little attention to the self-rescue mechanism. It is critical to understanding crowd evacuations and better response strategies. We modeled the Grenfell Tower (a high-rise building with a complicated structure) case in 2017. Based on the percolation and social force models, we build an agent-based model to simulate individual behaviors inside. We obtain the optimal solution and robust paralleled outcomes under all counterfactual situations based on precisely matching tangible case outcomes (fire duration, deaths, and injuries). For individuals, mastering self-rescue skills is better at reducing social losses (deaths & injuries). In terms of high-rise buildings design, the central alarm system is also useful to reduce them. Besides, the crowd evacuation guided by the social force model also reduces deaths & injuries. This work provides insight into better high-rise building design and practical response strategies for societies. The central alarm system and fire-proof materials should be used in high-rise buildings. The residents should have routine training in social force-based evacuations and survival (self-rescue) skills to better the evacuation process and outcome under natural disasters and social emergencies.

1. Introduction

High-rise buildings (towers) are commonly defined as residential structures with more than ten floors and other non-monolithic civil structures with a height of more than 24 m (Guan, 2019). As critical public safety cases, high-rise building fires are featured by rapid development, diverse factors, dynamical propagation paths, and evacuation difficulty (Liu et al., 2012). For cities worldwide, the tensions between limited space and more land demand become more severe, forcing cities to construct more multi-layer buildings. Thus, the risk of high-rise building fires has been enhanced. From 2009 to 2013, around 14,500 high-rise building fires occurred each year in the US. Each year, they have caused 40 resident deaths, 520 injuries, and property damage of 154 million dollars (Ahrens, 2016). Thus, some measures should be taken to mitigate the severe consequences of high-rise building fires. For these fires, the ignition source, combustible materials, and comburent are necessary pre-conditions (Liu et al., 2012). Meanwhile, preventing fire will be challenging if we do not pay sufficient attention to building materials, alarm systems, and evacuation strategies (Liu et al., 2012). Here, we focus on evacuation patterns of human behaviors, which are critical to saving more lives from the fire. For evacuations under high-rise building fires, scenarios are complex and diverse. Also, the flame and smoke can cause indirect harm to the people. Compared to regular fire cases, high-rise building fires have special features, such as crowd evacuation and self-rescue behaviors (Hu et al., 2017). In most situations, it is difficult for a professional rescue force (the firefighters) to get inside and save people trapped in the building by the fire at the earliest time. Hence, self-rescue behavior is essential and should be the optimal choice for individuals. Nowadays, as there are more high-rise building fires, more attention should be paid to self-rescue behaviors. In this work, we use computational method to reveal basic evacuation patterns, based on which we focus on the effects of self-rescue behaviors.

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https://doi.org/10.1016/j.engappai.2023.107401
Received 8 December 2022; Received in revised form 15 September 2023; Accepted 28 October 2023
Available online 2 November 2023

With no doubt, the motivation is to find ways to reduce social losses, such as deaths and injuries.

Research on high-rise building fires focuses on three domains: **(a) Numerical simulations of fire dynamics.** The Bayesian network has been used to simulate both two-way fires spreading to reveal fire dynamics (Cheng and Hadjisophocleous, 2011). The computational Fluid Dynamics (CFD) model is good at simulating evacuations under smoke in stairways (Chen et al., 2015). Both fires and explosions can be deemed as complex fluid flows. Hence, the fire may cause an explosion when certain conditions are met (Skjold et al., 2018). The turbulent indoor fires can be captured by the Fire Dynamics Simulator (FDS) (Ahn et al., 2019). **(b) High-rise building design.** The unreasonable design of high-rise buildings causes many social losses. The evacuation stairs and fire-fighting lift do not reach the ground floor (Ronchi and Nilsson, 2013). The stairs share the lobby with the fire-fighting lift (Ma and Guo, 2012). The stay-put tactic is obsolete and could lead to severe misjudgments (Arewa et al., 2021). Appropriate measures can be taken to better fire safety design, such as overall layout, evacuation stairways, and automatic alarm systems (Wang, 2012). Installing fire-fighting doors between stairways and floors can lead to more people using the stairs, which largely boosts evacuation (Rahouti et al., 2018). **(c) Individual behaviors.** The particle swarm algorithm optimization can be applied to model the leader of the crowd and evacuation path (Junaedi et al., 2013). The virtual reality (VR) system platform has been constructed and implemented for evacuation simulations, improving evacuation percentages of high-rise building fires (Zhang and Wang, 2012). Fire VR is ideal for understanding individual behaviors and improving safety levels (Çakiroğlu and Gökoğlu, 2019). Comparing VR systems and real fire case data, it seems that VR technology effectively captures humans' actual behaviors (Bourhim and Cherkaoui, 2020). In addition, this model implemented in MATLAB can also simulate the effects of fire on human movement and evacuation time (Benseghir et al., 2021). Some researchers propose a new integrated technological framework to improve fire situational awareness by combining VR with BIM (building information model), the Internet of Things (IoT), and Augmented Reality (AR) (Chen et al., 2021). However, previous mathematical and system dynamics models ignore social and human factors. AR/VR technology is expensive, and the gaps between the virtual and real world are still huge, and it is difficult to make individual experiences entirely consistent (Ding et al., 2021). Participants of the VR experiment know that it is not real (fatal). In collusion, most existing works focus on evacuations but less attention has been paid to self-rescue behaviors of microscopic agents. Meanwhile, these studies failed to demonstrate how macro-level emergence has been formed by micro-level individual interactions, which is the critical mechanism to understand crowd dynamics during fire evacuations (Daud and Rahman, 2020; Lu et al., 2021).

Previous works with the 2D model cannot accurately model the human behavior and evacuation experiment in the high-rise building fire simulation. To recapitulate the self-rescue behaviors more precisely, we build the multi-layer building with the 3D model in NetLogo software. We use the multi-agent system to model the crowd dynamics under the fire case. The agent-based modeling (ABM) compensates for the shortcomings above because: **(a) Procedural and Intrinsic Dynamics.** It provides procedural and dynamic analysis to model how subjects interact dynamically, which is often neglected by mathematical models and system dynamics (Waldrop, 2018; Zvereva, 2020). We provide agents with some rules that describe fundamental behaviors under emergency evacuation. **(b) Heterogeneous subjects and asymmetries.** Assumptions of homogeneity and symmetry simplify the calculations (Chattoe-Brown, 2013), but this is unreal. The properties of reality are often heterogeneous and asymmetric (Ormerod and Rosewell, 2006). In fire evacuation, individuals have asymmetric information and heterogeneous behaviors (Li and Han, 2015). The heterogeneity and asymmetry can be well described by Agent-Based-Modeling, which allows us to represent complex dynamic behaviors (Bonabeau, 2002). The properties of agents can be endowed to model human differences. **(c) Reproducibility.** ABM is highly reproducible. We inevitably obtain different outcomes under the same parameters, intelligent algorithms, and behavioral rules (Stieler et al., 2022). ABM can repeat the experiments and adjust parameter values to fit tangible outcomes (Devezer et al., 2019). Fewer studies have used ABM to explore the crowd dynamics of high-rise building fires. In this work, our ABM model also combines the percolation model (Beer, 1990) and a social force evacuation model (Thalmann et al., 2009) to simulate a real target case (the Grenfell Tower fire in 1967). We chose Grenfell Tower as our research case for three reasons. First, this fire case caused considerable casualties and severe impacts on society. Second, we feel interested in potential associations between factors such as building structure, fire-proof design, stay-put policy, and the fire outcome, which this case can fully provide. Third, its complex structure makes it difficult for external rescue to reach in time, which is ideal to investigate self-rescue behaviors under fire. The macroscopic pattern of self-rescue can be modeled by individual behaviors and interactions (Condorelli, 2016). Based on real target case, we therefore add heterogeneity and interactions to reveal the mechanism of self-rescue behaviors.

2. Methods and materials

2.1. Agent-based modeling (ABM)

Agent-based modeling (ABM) has a rich development history that spans multiple disciplines and decades. The early classic application comprises the Cellular Automata (CA) and artificial life. For example, Schelling's segregation model demonstrates the segregation rule in race and income (Bullinger et al., 2021). ABM has gained increasing acceptance and recognition in architecture and fire dynamics (Bankes, 2002). The dynamics of high-rise building fires can be conceptualized as complex systems. The main characteristics of complex systems are the non-linear relationship between the interactions among constituent elements at a micro-level and the resulting micro-macro effects (emergence) (Stieler et al., 2022). ABM has been implemented in various research projects to reveal non-linear relationships, emergence, and inherent complexity in architectural structures and fire dynamics (Kaur and Kaur, 2022). Moreover, ABM is also extensively applied in other natural and social sciences, including the epidemiology of public health (Tracy et al., 2018), consumption systems (Micolier et al., 2019), acts of terrorism (Lu et al., 2021), resource recycling (Farahbakhsh et al., 2023), and collective motion (Lu et al., 2023). In addition to academic research, ABM software can be integrated with Building Information Modeling (BIM) and Computer-Aided Design (CAD) platforms, indicating that ABM is applied in practice (Beyaz et al., 2021). We use ABM to model and predict complex systems of high-rise building fire, exploring "what-if" scenarios and informing policy-making processes.

2.2. Real target case

The Grenfell Tower fire, a real target case of our ABM simulation, was caused by poor designs and weak modern warning equipment. The Grenfell Tower was built in 1967 and has a height of 220 feet 10 inches, 67.30 m. The design is under the **"stay-put policy"** idea, which uses walls and doors (exits) to segregate fire spreading. This tower did have smoke alarms but without a central alarm system. Besides, the material's flammability contributes to the rapid spreading of fire, and external cladding materials were also unsafe. Apart from the materials used, we focus on crowd dynamics and self-rescue behaviors during the evacuation. We use NetLogo to build a virtual environment based on real case data: **(a) Structure map.** As in Fig. 1, floors 1 to 4 were for non-residential (commercial) purposes, and 5 to 24 were residential floors. Each residential floor has six units and one public lobby. In the center, the hall is evenly surrounded by six flats (units). Elevators and stairways are located on the west and east sides of the hall. Later, the two lower

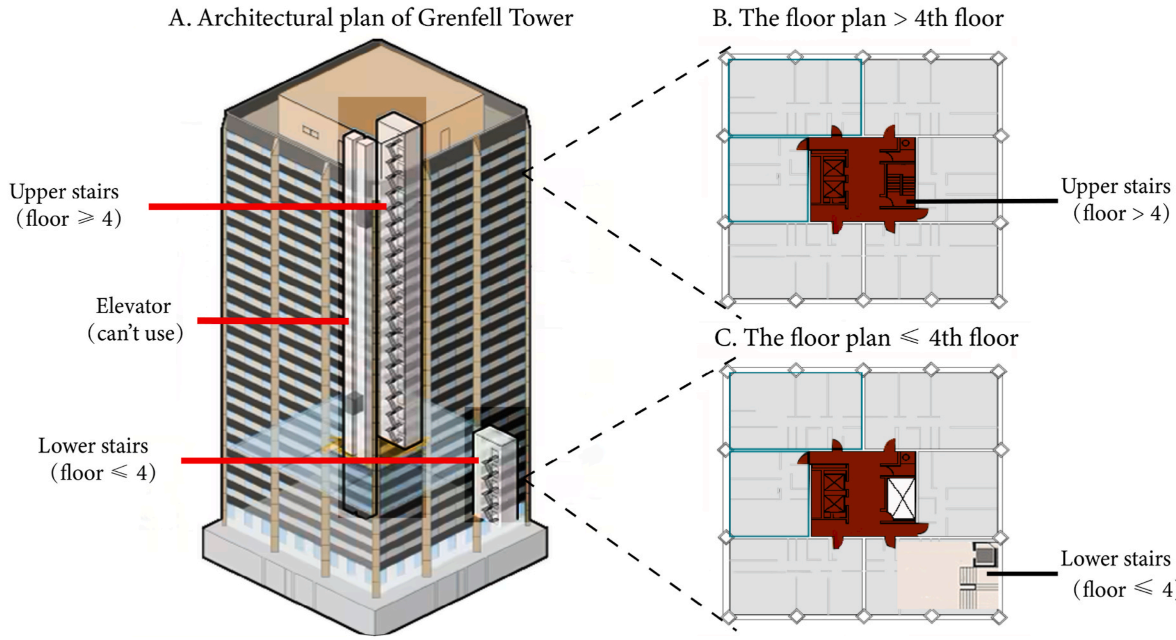

Fig. 1. Three-dimensional (3D) structure and floor maps of the Grenfell Tower. Panel A is the 3D diorama of Grenfell Tower. Panel B is the floor plan above the fourth floor. Panel C is the floor plan below the fourth floor. We obtained and modified Panels A, B, and C via the websites of Architizer (http://www.architizer.com) and FT (http://www.ft.com).

floors (from 3 to 4) were converted into residential floors. There are two stairways in total. The upper stairway for floors 5 to 24 is in the hall, while floors 3 and 4 are unique because one flat (at the southeast corner) was converted into the stairway. Consequently, floors (3–4) have five flats, and the stairway is in the southeast corner. According to Fig. 1, we construct the 3D model. **(b) Duration.** On June 14, 2017, the fire broke out in Grenfell Tower at 01:18. From 01:18 to 08:07, this process lasted for 7 h, which was $t \approx 420$ minutes. For our simulation, this duration should be precisely matched. Due to the chimney and buoyancy effects (Zhang and Wang, 2013), the smoke can move quickly in the elevator shaft. Therefore, it is dangerous to use the elevator, and residents can only escape via the stairway. **(c) Firing process.** The spreading process contains the first vertical phase (from the 4th floor to the top floor) and the second horizontal phase (it spreads widely on each floor). The initial fire (flame) was from flat 16 on the 4th floor at 00:54 because a refrigerator went wrong. Then, it broke through the window at 01:08 and ignited the (flammable) cladding. At 01:07, firefighters entered this flat but failed to control the spreading. From 01:15 to 01:30, it spread quickly and vertically onto the top floors. From 01:36 to 04:00, it began to spread horizontally inside each floor. From 04:00 to 08:00, the fire affected all sides of the building. It continued to burn until the night of June 16. The entire process lasted approximately 60 h. So, our model should match the main period of crowd evacuation (from 01:18 to 08:07), and 420 min can be defined as reasonable. **(d) Social damage outcomes**. When the fire began to spread, more people perceived this risk information and tried to escape. For most tall building cases, the role played by firefighters is limited (Kodur et al., 2020). They cannot effectively rescue residents of the middle and upper floors because of the high altitude and severity of the fire. Although firefighters had rescued some survivors on lower floors, the evacuation was the key to escape successfully. Eventually, this fire caused 72 deaths and 74 injuries, with 233 residents escaped. This real outcome should be precisely matched by our simulation. Due to the limited capabilities of firefighters in related cases, they are not included in our model. In this case, people should mainly rely heavily on self-rescue behaviors. In our agent-based model, we have adequately considered mechanisms of perceived risk information, evacuation behaviors, and self-rescued skills during the evacuation process.

2.3. *Basic model settings*

It contains **(a) Fire spreading**. The rate of fire spread is critical for modeling the high-rise building fire related to combustion and spatial characteristics (Cheng and Hadjisophocleous, 2011). Based on the previous fire dynamics simulator (FPS) model (Cheng and Hadjisophocleous, 2011; Yi et al., 2019), we simplified the fire spread as equation (1) to model both vertical and horizontal spreading patterns. The Q_f represents the area of fire spread, t_0 is the initial time of fire, t is the duration of fire burning, and α is the fire spread factor. In the case of Grenfell Tower fire, the vertical and horizontal spread speeds are different. For the initial phase, the vertical spread is much faster. In our model, the flame breaks out in flat 16 on the 4th floor. Then, it spreads everywhere inside the room. After the fire broke through the windows and ignited the cladding, it spread vertically upwardly. According to the report (Guillaume et al., 2020), it reached the top floor within 40 min, and the entire northeast corner became a complete vertical fire. The vertical distance above the fire was probably 55 m. The rate α of vertical spread is 0.65. Vertical speed on different floors is similar for the same aluminum sandwich plates (McKenna et al., 2019). We simplified external factors such as wind speed, windows, and fire protection. The model simulated the vertical spread with uniform velocity (Guillaume et al., 2020). The horizontal spread dominates after the vertical spread phase (Guillaume et al., 2020). At more than 50 m in height, the speed is unaffected by external factors (wind, windows, and fire suppression). The rate α of horizontal spread is about 0.293 ± 0.005. The speed at the height of fewer than 50 m is more susceptible to external factors, which is also difficult to measure. Given it is hard to determine (measure) the speed, we simplified it as a uniform speed in our model (Guillaume et al., 2020).

$$Q_f = \alpha(t - t_0)^2 \tag{1}$$

(b) Size and attributions of agents. In our real target case, the building had 293 residents in total. So, we set the same number of agents or residents (N=293) in our model. We assumed they were randomly distributed among the rooms on each floor because related information is hard to obtain. The health status indicator should be set to indicate the death, injuries, or health of all residents at each time (t). This indicator is critical to modeling the dynamic status of all agents or residents, and we use the levels of $Blood_i^t$ to indicate the dynamical health status, at the time of t, of heterogeneous agents (i) during the whole process. Related National data can be used to model the health distribution of $Blood_i^t$, in the population. According to the 2021 UK Census, we choose the age distribution to model the residents of the Grenfell Tower. As the age is roughly normally distributed, we set initial levels ($Blood_i^0$) to obey the normal distribution, such as $mean = 100$ and $SD = 20$, based on equation (2).

$$Blood_i^0 = \frac{1}{\sqrt{2\pi}\sigma} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) = \frac{1}{\sqrt{2\pi} \bullet 20} exp\left(-\frac{(x-100)^2}{2 \bullet 20^2}\right) \quad (2)$$

(c) Fire and smoke damages. It is difficult to quantify the damage caused by flames and smoke. We calculate this based on a real case target: most survivors were evacuated from the tower within 3 h of the fire. The impacts of smoke on the human body require calculating carboxyhemoglobin concentration in the blood. However, this is a cumulative process. We consider the time of the last survivor to be rescued as $T = \max(t)$. In the real target case, the last survivor was rescued within 7 h ($T \approx 420$ minutes). So, we set the smoke damage ($Smoke_{Dam}$) as 0.22 (blood per minute). We also define fire damage. The ambient temperature rises with a significant heat release. During the evacuation, residents' skin and respiratory tract were directly in contact with the flames. The body burns, skin & respiratory tract damage, and gradual loss of mobility happened. The fire damage can be calculated ("Population Characteristics," 2019) in equation (3). The $Fire_{Dam}$ represents the damage caused by the fire within short time (0–1 min). The $T_{average}$ represents the average temperature around an individual within a short time (0–1 min). In the real target case, the average temperature could be over 400 °C. In our model, we calculate the damage caused by the fire as 0.48 blood per minute.

$$Fire_{Dam} = 5 * 10^{22}\left(T_{average}\right)^{-11.783} + 3 * 10^7\left(T_{average}\right)^{-2.9636} \quad (3)$$

2.4. Self-rescue behavior settings

Self-rescue means that residents can save themselves in emergencies (Bris et al., 2009). Most studies focus on position changes from hazardous to safer areas (Bris et al., 2009; Liang et al., 2022). Our model describes the microscopic behaviors of agents in detail, such as perceiving fire information, social force effects, and the immunity of survival skills to damage:

(a) **The evacuation speeds.** In this case, self-rescue behavior is to go downstairs and escape quickly. Two stairways are at different locations, dividing the process into two stages. They should change the stairway on the fourth floor, which increases the evacuation difficulty. Based on existing research, horizontal speed is approximately 2–3 times vertical speed (Ding et al., 2021). So, the horizontal movement speed should be between 0.5 and 1 m per minute. We do not know the speed for our case, so we take the time when most survivors escaped (about 3 h) to calculate vertical speed. So, the vertical speed is about 0.35 m per minute.

(b) **The delay time.** Time is one of the key factors for the self-rescue of agents. The sooner the fire information is perceived, the earlier evacuation decisions can be made. Residents planned their escape routes and methods based on the heterogeneous fire information. Accordingly, we set the delay time mechanism to represent the heterogeneous fire information and individual panic state in equation (4). The fire occurred at night without a central alarm system. Many residents were unaware of it until it was close to their floors. We define this period as perception time ($T_{Perceive}$). After perceiving the fire, individuals often panic; mild panic is conducive to rapid decision-making, while excessive panic will increase evacuation time (Shang et al., 2023). In our model, we assume that the extent of panic is related to the height of the floor. In other words, the higher the floor, the more intense the panic mood of the agent, and they will hesitate to escape, which leads to the delay time increase. We define this period as decision time ($T_{Decision}$). In summary, the delay time (T_{Delay}) is made up of two parts in equation (4). We consider $T_{Perceive}$ to be simultaneous with the vertical spread, so we set a random number (between 0 and 35) as the perception time. And $T_{Decision}$ is related to the vertical distance from the agents to the fourth floor.

$$T_{Delay} = T_{Perceive} + T_{Decision} \quad (4)$$

$$Moving = \begin{cases} \overrightarrow{F_1} = \left(\overrightarrow{A_0} - \frac{\sum_{i=1}^{N_1}\overrightarrow{A_i}}{N}\right) \overrightarrow{F_2} = \overrightarrow{\theta_0}\, \overrightarrow{F_3} = \sum_{i=1}^{N_1} \frac{1}{\left(\overrightarrow{A_0} - \overrightarrow{A_i}\right)} F_4 = \frac{dv_i(t)}{dt} = \frac{1}{i} * \sum_{i=1}^{N_1}(V_i - V_0) \end{cases} \quad (5)$$

$$Blood_i^t = Blood_i^o - \left(\sum\nolimits_0^t Smoke_{Dam} + \sum\nolimits_0^t Flame_{Dam} - \lambda\right)$$

$$State = \begin{cases} Normal\ ,\ if Blood_i^t \geq 60\% * Blood_i^o \\ Injured, if\ Blood_i^t < 60\% * Blood_i^o \\ Death, if\ Blood_i^t \leq 0 \end{cases} \quad (6)$$

(c) **Stairway behaviors.** Because of the limited space in the stairway and the smoke, they inevitably tend to push and shove during the evacuation, which reduces evacuation efficiency and will lead to injuries and deaths. We defined this pattern as normal evacuation. The second pattern is based on the extended social force model, which belongs to discrete models of pedestrian dynamics (Sticco et al., 2021). It has been revised, extended, and improved several times (Helbing and Molnár, 1995). It considers social and physical factors to demonstrate subjective conscious reflections of real people (Lu et al., 2021). This model can be applied in various evacuation scenarios, such as subway stations (Qu et al., 2014), smoke spreading (Makmul, 2020), and residential buildings (Choi et al., 2014). Existing social force models rarely deal with stairway evacuations and neglect the effect of individual speed during going down the stairs (Wang and Weng, 2014). So, we proposed an extended social force model to model stairway actions. Four social forces ($\overrightarrow{F_1}$, $\overrightarrow{F_2}$, $\overrightarrow{F_3}$, F_4) are applied in equation (5). The cohesion force ($\overrightarrow{F_1}$) makes agents move towards the group, which forms small groups. The navigation force ($\overrightarrow{F_2}$) calculates vector direction between people and the exits. The separation force ($\overrightarrow{F_3}$) calculates the distance between an individual and others and enables individuals to avoid shoving and pushing in descending stairs. While going down the stairs, the factors of forwarding speed, gravitational acceleration, and landing floor of stairs cause people to push and shove others (Zeng et al., 2018). The control of one's speed in stair evacuation is significant compared to the flat ground because the collisions on stairs make falls and stampedes much easier than other situations. We proposed the social force (F_4) to calculate the average moving speed of the crowd. Three vector forces ($\overrightarrow{F_1}$, $\overrightarrow{F_2}$, $\overrightarrow{F_3}$) calculate the moving direction, and the non-vector forces (F_4) determine the moving speed. As Fig. 2B & D show, they ($\overrightarrow{F_1}$, $\overrightarrow{F_2}$, $\overrightarrow{F_3}$, F_4) jointly determine how they moves in the space of stairways. We will compare outcomes of both normal evacuation and social force evacuation patterns.

(d) **Health dynamics and self-rescue survival skills.** In equation (6), the $Blood_i^t$ represents the dynamical health status of agent *i* at the moment *t*. The $Blood_i^o$ represents initial blood, which follows the normal distribution. The $\sum_0^t Smoke_{Damage}$ denotes the smoke damage from the start to (t). The $\sum_0^t Flame_{Damage}$ denotes the fire damage caused. The agent will be damaged if the agent is less than 1 m from the fire. The smoke continuously harms each agent after the fire completes its vertical spread phase. Meanwhile, survival skills (λ) can reduce the damage caused by fire and smoke. We set the agent to die when its blood value reaches zero. If the blood value falls below 60% of the initial blood value, we define the injury of agents. Under harsh fire scenarios, they reduce fire and smoke damage through survival skills. In the real target case, some residents have little knowledge of these skills. Alternatively, they know but cannot use them properly. We set the survival skills factor as the term λ. In our model, residents can use survival skills to reduce the damage caused by fire and smoke. The fire damage immunity is from {0.1, 0.2, 0.3, 0.4}, and smoke damage immunity is from {0.05, 0.1, 0.15, 0.2}. With better skills, agents will bear more damage in the fire.

(e) **Single-damage immunity and dual-damage immunity patterns.** This setting is based on the previous rule. First, the individual only takes damage from fire or smoke in a single-damage immunity pattern. As shown in equation (5), in the fire immunity pattern, the agent will be continuously damaged by the smoke, but different immunity degrees to the fire damage, such as $\lambda \in \{0.1, 0.2, 0.3, 0.4\}$, can be achieved according to individual self-rescue survival skills (survivability). For the smoke immunity

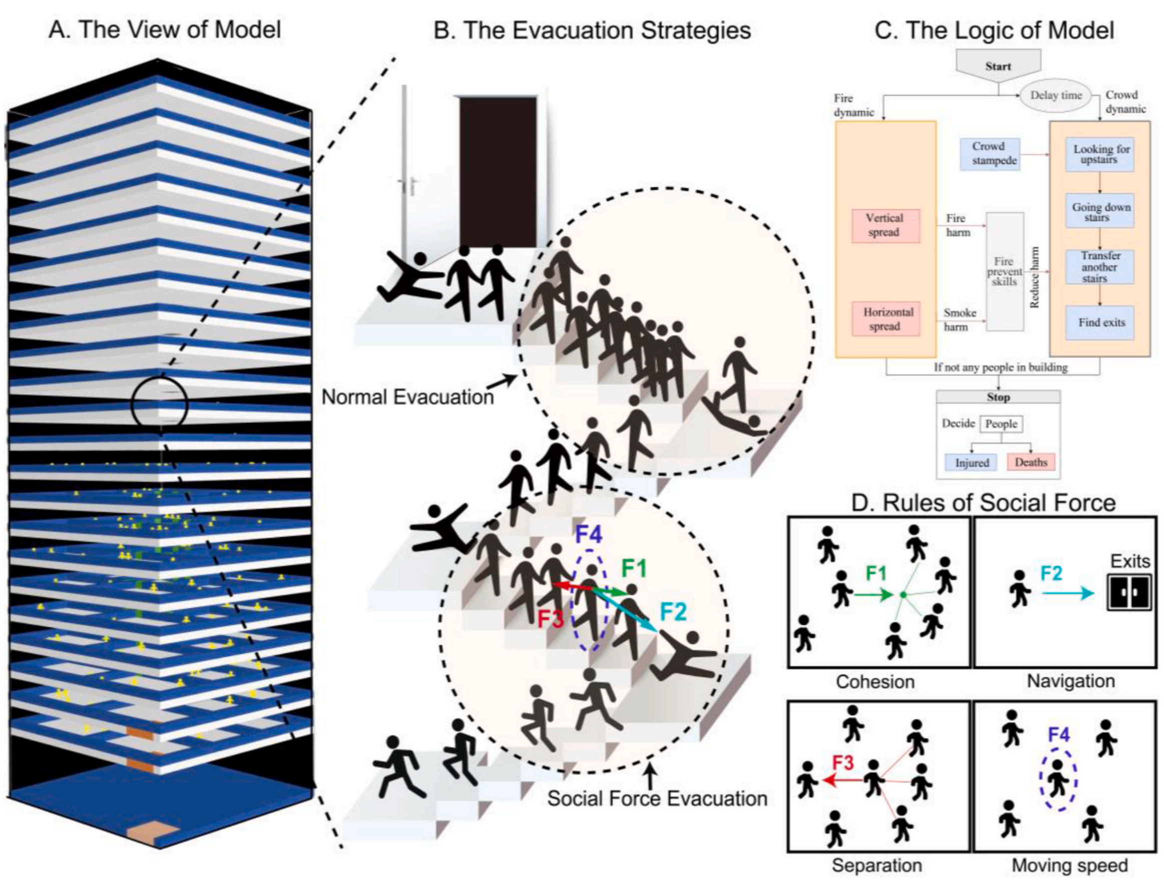

Fig. 2. The interface and logic of the model. Panel A shows the view of the model, visualizing the high-rise building and its residents. Panel B shows the evacuation process on the stairs, including normal evacuation and social force evacuation. Panel C shows the logic of the model, including the causal relationship between different variables. Panel D shows the rule of social force evacuation. Cohesion is towards the average position of residents. Navigation is towards the exits. Separation avoids collisions. Moving speed determines the average speed of the group.

Table 1
Parameter values of simulations.

Parameters		Interpretations	Initial Value	Value Ranges
Group size (N)		The number of residents	293	$\{200, 220, 240\ldots, 400\}$
$Blood_i^o$		The initial blood distribution	$Blood_i^o \sim N(100\ ,\ 20^2)$	$Blood_i^o \sim N(100\ ,\ 20^2)$
$Blood_i^t$		The value of blood in t	\	$[0\ ,\ Blood_i^o]$
The speed of agents (v)	Horizontal (v_{Hor})	The horizontal speed	$0.5 + s \in (0, 0.5)\ m/min$	A float number from the set [0.5, 1]
	Vertical (v_{Ver})	The vertical speed	$0.35\ m/min$	0.35
Damage	Fire ($Fire_{Dam}$)	Blood loss (Close to fire)	0.48	0.48
	Smoke ($Smoke_{Dam}$)	Blood loss (Inhalation)	0.22	0.22
Damage (Pushing and shoving)	Pusher	Blood loss	0.1	0.1
	Pushed	Blood loss	0.2	0.2
Falling distance from the height	Pusher	No change	0	0
	Pushed (d_{fall})	Location drops	0.7	0.7
Alarm	True	Simulation (With a central alarm system)	\	Information homogeneity
	False	Reality (Without)	\	Information heterogeneity
Evacuation strategies	Panicky	Reality (pushing and shoving)	\	Blood loss and location change
	Rational	Sim (No pushing or shoving)	\	\
Survival skills		Percentage of skilled agents	0%	$\{20\%, 40\%, \ldots 100\%\}$
Damage reduction	Fire	Reduce damage from fire	0.00	$\{0.1, 0.2, 0.3, 0.4\}$
	Smoke	Reduce damage from smoke	0.00	$\{0.05, 0.10, 0.15, 0.20\}$

pattern, if the individual is 1 m from the fire, this agent suffers from the damage caused by the fire. According to individual survivability, different immunity degrees to smoke damage, such as $\lambda \in \{0.05, 0.1, 0.15, 0.2\}$, applies to different agents. Second, for dual-damage immunity pattern of agents, they have different immunity degrees to both fire damage, such as $\lambda \in \{0.1, 0.2, 0.3, 0.4\}$, and the smoke damage, such as $\lambda \in \{0.05, 0.1, 0.15, 0.2\}$, according to different agents.

3. Optimal solution outcomes

3.1. Best-fitting solution

We compare simulation outcomes with the real target case', to examine the validity and robustness of our solution. In the NetLogo, we constructed a high-rise building with 24 floors, which is a complex multi-agent system with 293 agents or residents. Therefore, critical data of the real target case should be matched by our simulation as closely as possible. Key indicators can be y_1 (total duration), y_2 (number of deaths) and y_3 (number of injuries). According to all parameter value ranges in Table 1, we iterate all combinations of parameters to search for the optimal solution. We repeat each combination (simulation) 200 times to obtain robust outcomes, such as average duration ($\hat{y}_1$), average deaths ($\hat{y}_2$) and average injuries ($\hat{y}_3$). Based on real case data, we obtain observed values, which jointly form our real case function of $f_{real}(\bullet) = Y_i = \{420,\ 70,\ 74\}$. We obtain robust results from 200 repeated simulations and construct the simulated function of $f_{sim}(\bullet) = \{\hat{y}_1, \hat{y}_2, \hat{y}_3\}$. In equation (6), we calculate the difference Δ between both simulated and real case functions. Under the minimal gap (Δ), we can solve the best-fitting combination of parameter values, which can be deemed as an optimal solution $Par^*(\bullet)$, which reflects real-world crowd dynamics.

$$Par^*(\bullet) = ArgMin(\Delta) = ArgMin[f_{sim}(\bullet) - f_{real}(\bullet)]$$

$$= ArgMin\left(\sqrt{\frac{\sum(\hat{y}_1 - 420)^2}{200}} + \sqrt{\frac{\sum(\hat{y}_2 - 70)^2}{200}} + \sqrt{\frac{\sum(\hat{y}_3 - 74)^2}{200}}\right) \quad (7)$$

3.2. Validity and robustness supported

We use validity and robustness (two standards) to verify our optimal solution. The validity requires that the simulated outcomes can precisely match the real target case, such as total duration (y_1), resident deaths (y_2), resident injuries (y_3). The robustness means that this fitting degree should be stable and more probable. In other words, the distribution (N=200) should be bell-curved and symmetric to the mean value, i.e., as close to the real target case as possible. It seems that our optimal solution has precisely matched real case outcomes in total duration (y_1), resident deaths (y_2), resident injuries (y_3).

(a) Robust fitting of total duration (y_1). The fire-burning process takes 7 h (420 min) in total. In NetLogo, we use 1 min as one tick in our simulation. As shown in Fig. 3A, the average duration is

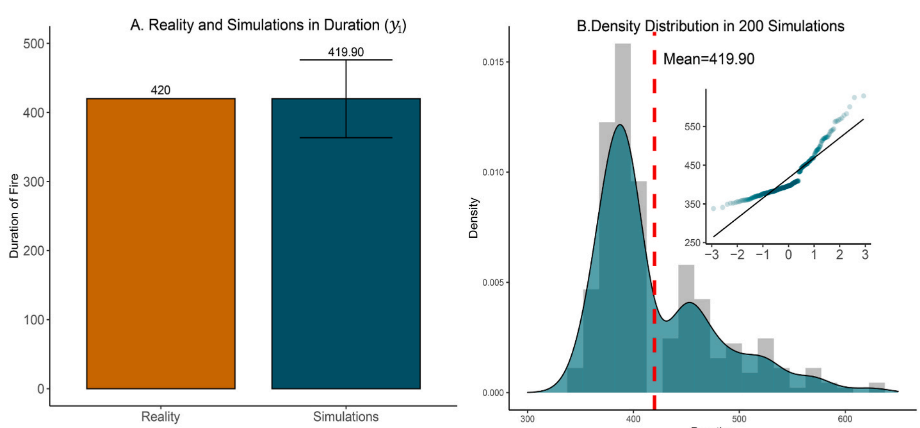

Fig. 3. Comparison between real-life duration and simulations. Fig. 3A shows the real duration and the average duration of simulations. Fig. 3B visualizes the probability density distribution of simulations, and the result of 200 simulations is a nearly normal distribution.

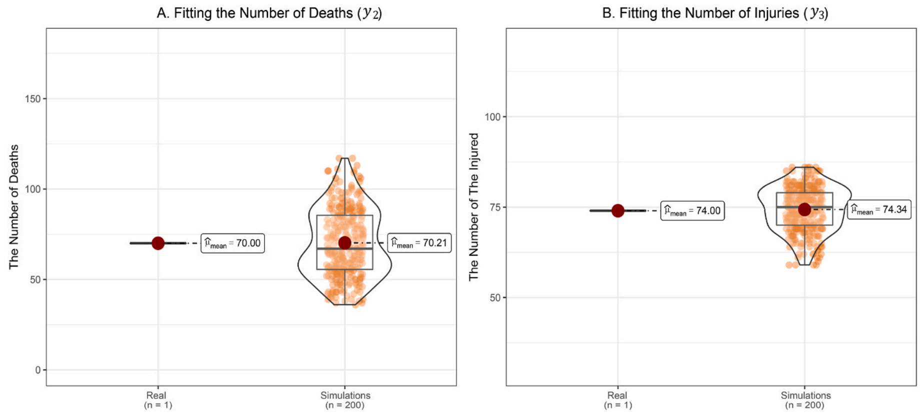

Fig. 4. The fitness between real deaths and injuries. Panel A shows the fitting of deaths, while Panel B shows the fitting of injuries. The violin plot shows the samples' mean ($\widehat{\mu}_{mean}$), descriptive statistics, and density distribution.

$\widehat{y}_1 = 419.90 \approx 420$ ticks (N=200), which equals $y_1 = 420$ min (7 h) for our real target case. It means that our optimal solution, $Par^*(\bullet)$, satisfies the standard of validity. In Fig. 3B, the distribution of simulation ticks roughly follows a Poisson distribution, which indicates the complexity of individual behavior patterns (Barabasi, 2005). Given the mean value of 419.90, the standard deviation (SD) is 56.38 (N=200), which is much less than the mean value. Most data points for the Q-Q normal plot are close to the straight 45°line. The real case value of 420 is also close to the mode value (419.90). Therefore, both the validity and robustness of the $Par^*(\bullet)$ can be supported, in terms of total duration (y_1).

(b) Robust fitting of deaths (y_2) & injuries (y_3). For the real target case (Watt, 2017), the fire caused 70 deaths (y_2) and 74 injuries (y_3), which have been precisely and robustly matched as well. In Fig. 4A, the mean value is $\widehat{y}_2 = 70.21$ (N=200), which equals the number ($y_2 = 70$) for the real target case. The standard deviation (SD) of 200 repeated simulations is 18.85, much less than the mean (70.21). Therefore, the validity of simulated deaths can be supported. To check the robustness, the violin plot in Fig. 4A shows that most data points are well within the normal value range. So, the robustness can be supported as well. In Fig. 4B, average resident injuries can be $\widehat{y}_3 = 74.34$ (N=200), which equals the number in our real target case ($y_3 = 74$). In addition, the standard deviation (SD) can be 6.2, which is much smaller than the mean of 74.34. So, the validity of simulated injuries can be well held by our optimal solution. The violin plot in Fig. 3B indicates that most data points are well within the normal value range, which also supports the robustness of our simulated injuries. Thus, our optimal solution, under 200 repeated simulations, has shown both validity and robustness of simulation outcomes in terms of fitting real case outcomes.

4. Counterfactual experiments

Given both the validity and robustness of our optimal solution, it can be concluded that it has dramatically captured the real-world behavior patterns of individuals and the crowd. Based on the optimal solution of $Par^*(\bullet)$, we traverse other parameter values (see Table 1) to obtain counterfactual outcomes. As well, we repeat each simulation by 200 times to obtain robust outcomes of $\widehat{y}_1$, $\widehat{y}_2$ and $\widehat{y}_3$.

4.1. Impacts of the alarm designs

In this real case, the alarm design is unreasonable because it does not have a central alarm system. If a fire breaks out, the residents cannot be notified in time, significantly affecting the self-rescue process and final results. Meanwhile, we infer the outcome of reasonable alarm design, with a central alarm system installed in the high-rise building. We compare both real case situation (without) and counterfactual situation (with), and it seems that: **(a) The number of deaths (y_2) can be exactly reduced by the practical design of a central alarm system.** The practical design often has a central alarm. In an environment with a central alarm system, the ability of individuals to perceive a fire is greatly enhanced. Everyone can perceive the fire at once. Fig. 5 shows the result with a central alarm system. In Fig. 5, the percentage of deaths with a central alarm is always lower than without a central alarm. For different groups, the percentage of deaths increases as the group number increases. In Fig. 5A, for a group of 200, the percentage of deaths without a central alarm is 17.87%, while the percentage of deaths with a central alarm is only 11.32%. In contrast, for a group of 400 residents,

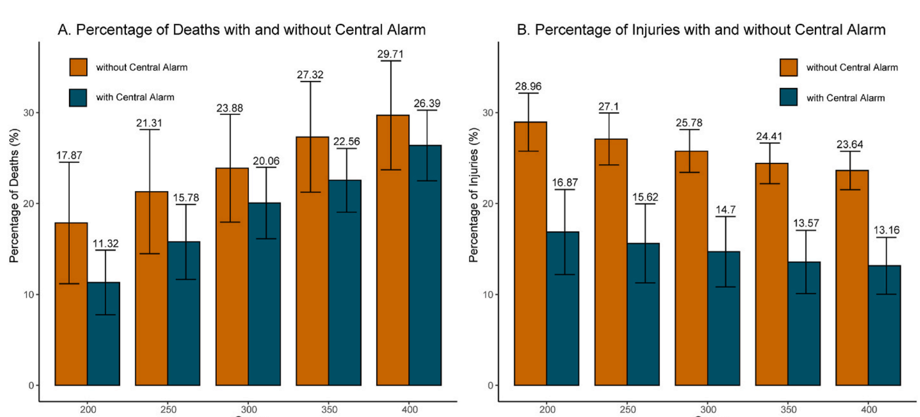

Fig. 5. The impact of fire with and without an alarm on the percentage of deaths and injuries. Panels A & B compare the death & injury percentages with and without the central alarm system.

the percentage of deaths without a central alarm is 29.71%, while the percentage of deaths with a central alarm is only 26.39%. It demonstrates that the percentage of deaths increases as the group number increases, and the difference between the percentages of deaths gradually decreases. **(b) The number of injuries (y_3) can also be exactly reduced by the practical design of a central alarm system.** In Fig. 5B, for a group of 200 residents, the percentage of injuries without a central alarm is 28.96%, while the percentage of injuries with a central alarm is only 16.87%. On the other hand, for a group of 400 residents, the percentage of injuries without a central alarm is 23.64%, while the percentage of injuries with a central alarm is only 13.16%. It shows that the percentage of injuries decreases as the group number increases, and the difference between the percentage of injuries gradually decreases. In a word, it is clear that fewer residents are injured in groups with central alarms than in groups of the same size but without these alarms. A central alarm system can reduce the percentage of injuries in a fire evacuation, but the effect of the alarm decreases as the group number increases.

4.2. Outcomes of different evacuation strategies

During the evacuation, crowding and shoving always occur and cause damage to others, which is especially significant when escaping downward the stairway. We simulate the mechanism of crowd shoving and compare deaths under normal escape and social force models. We compare deaths between normal (random) evacuation and social force mode strategies in Fig. 6. Besides, we distinguish two situations, without (real case) and with a central alarm system (counter-fact).

(a) The deaths (y_2) can be substantially reduced as the agents apply social force mode, compared to random evacuations. We first compare the death percentages in Fig. 6A & C. The percentage of deaths can be reduced substantially for the real target case (without a central alarm system). Fig. 6A shows that the percentage is 23.96% (SD=7.75), which has been reduced to 13.34% (SD=6.44%) in Fig. 6C. Thus, the two values are significantly different from each other in statistics. For the counter-fact of this case (with a central alarm system), the percentage is 18.63% (SD=3.41%), which has decreased to 4.21% (SD=3.4%) in Fig. 6C. Similarly, the two values are significantly different from each other in statistics. Thus, we have two findings: the death can be reduced if the agents use social force mode during the fire evacuation. This pattern is robust, whether we have installed a central alarm system in this high-rise building. Fig. 6 proves the evacuation effectiveness under the social force strategy. In practice, the social force mode can be enhanced by training, which governments, companies, or institutions can organize well.

(b) The injuries (y_3) can be slightly increased when the agents apply social force mode, compared to normal evacuation. Then, we compare the percentages of injuries between the normal evacuation strategy and the social force model in Fig. 6B & D. Meanwhile, we also distinguish two situations, Without (real case) and With the central alarm system (counter-fact). It seems in Fig. 6B that the injury percentage is 25.37% (SD=2.49%) under random evacuation mode, which then grows slightly to 30.7% (SD=2.11%) in Fig. 6D. In statistics, the two values are not significantly different, meaning the change is small for the injury. For the counter-fact of this case (with a central alarm system), the injury percentage is 14.43% (SD=5.52%) and grows slightly to 18.65 % (SD=4.01%). Statistically, these two values are also not significantly different from each other. Thus, we have two findings: The injury can be slightly or little increased if they use social force mode during the evacuation. This pattern is robust, regardless of whether we have installed the central alarm system. Fig. 6 proves the evacuation effectiveness under a social force model-led strategy. Although the

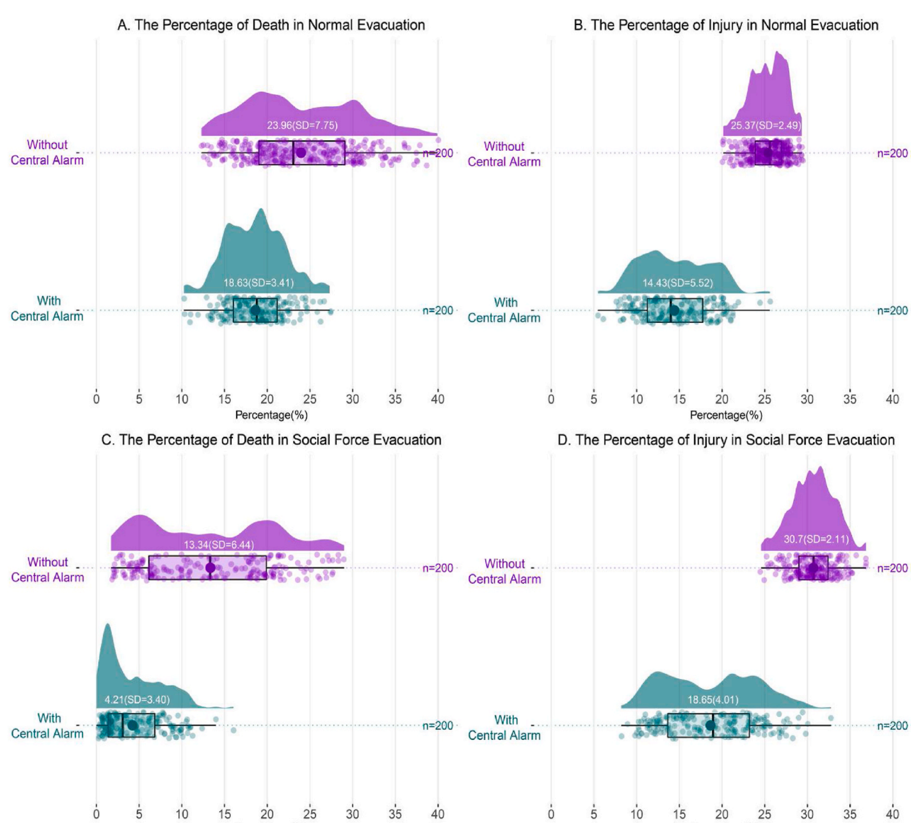

Fig. 6. The impact of normal evacuation and social force evacuation. Panels A & C show the percentage of deaths under different evacuation strategies with and without alarms. Panels B & D show the percentage of injuries under different evacuation strategies with and without alarms. The box plot is the descriptive statistics of the samples, and the cloud plot represents the density distribution.

injury is not heavily reduced, the deaths have been greatly reduced.

4.3. Single-damage immunity pattern

Generally, fire and smoke can cause harm or even lead to death for people during a fire evacuation. We introduce two survival skills to resist smoke and fire damage (damage immunity of smoke and fire) and explore the impact of two survival skills. Survival skills can significantly influence individual behaviors (Houvouras IV & Harvey, 2014), survival methods (McLennan et al., 2019), and evacuation strategies (Rüppel and Schatz, 2011) of people in the fire. Behavioral skills training (BST) is practical for obtaining survival skills and improving individuals' safety (Cakiroglu and Gokoglu, 2019; Houvouras IV and Harvey, 2014). In reality, some residents may have applied some survival skills, but it is unclear and not well-trained. In our agent-based modeling, we assume they got the BST and learned survival skills. We introduce fire-immune and smoke-immune modes to investigate further the relationships between fire damage, smoke damage, and survival skills. We discuss two situations. First, we only consider the fire damage, ignoring smoke damage. Second, we only consider the smoke damage, ignoring fire damage. For the people, the usage of survival skills equals the value of fire damage immunity, with four levels in {0.1, 0.2, 0.3, 0.4}; and the damage immunity value of smoke is from {0.05, 0.1, 0.15, 0.2}. It suggests that:

(a) **Fire immunity dramatically reduces deaths (y_2).** In this situation, we only consider the fire damage and ignore the smoke damage. We use real case outcomes as the baseline levels. In Fig. 7A, the percentage of deaths is 23.89% (real case). Under the pattern of fire immunity, we explore the effects of survivability (percentage of agents with survival skills) and different levels of fire damage immunity. It seems in Fig. 7A that either growing fire damage immunity or growing survivability leads to a decline in the percentage of deaths. For example, if we fix the damage immunity of fire on 0.4, the deaths are 21.91%, while 20% of people have survival skills to resist fire damage. In contrast, the deaths are 16.13%, when 100% of people have survival skills to reduce fire damage. It indicates that residents using appropriate survival strategies can reduce the deaths caused by the fire. Therefore, more residents survived after the fire, although they were all injured to different degrees.

(b) **Smoke immunity reduces deaths (y_2) slightly.** In this situation, we only consider the smoke damage and ignore fire damage. Fig. 7B shows that as the percentage of survivability grows, the percentage of deaths decreases. For example, if we fix the damage immunity of smoke at 0.2, the deaths will decrease from 21.79% to 17.13%, and the injuries will decline from 26.28% to 25.02%. It indicates a different trend between fire damage and smoke damage. Regarding the percentage of deaths, all residents have a relatively lower percentage of deaths compared to the real target case. As residents in the fire use survival skills to reduce the damage caused by the smoke, more residents can survive. The percentage of injured agents decreases as the percentage of skilled agents increases because more residents can use survival methods to protect themselves from the damage caused by smoke.

(c) **Both two immunity skills will increase survival duration (y_1).** Fig. 7C indicates that as the percentage of residents with skills increases, the survival time (y_1) also increases gradually. Meanwhile, the survival time (y_1) becomes longer as the damage immunity level grows. From the comparison between the two patterns, we conclude that survival skills could enable residents

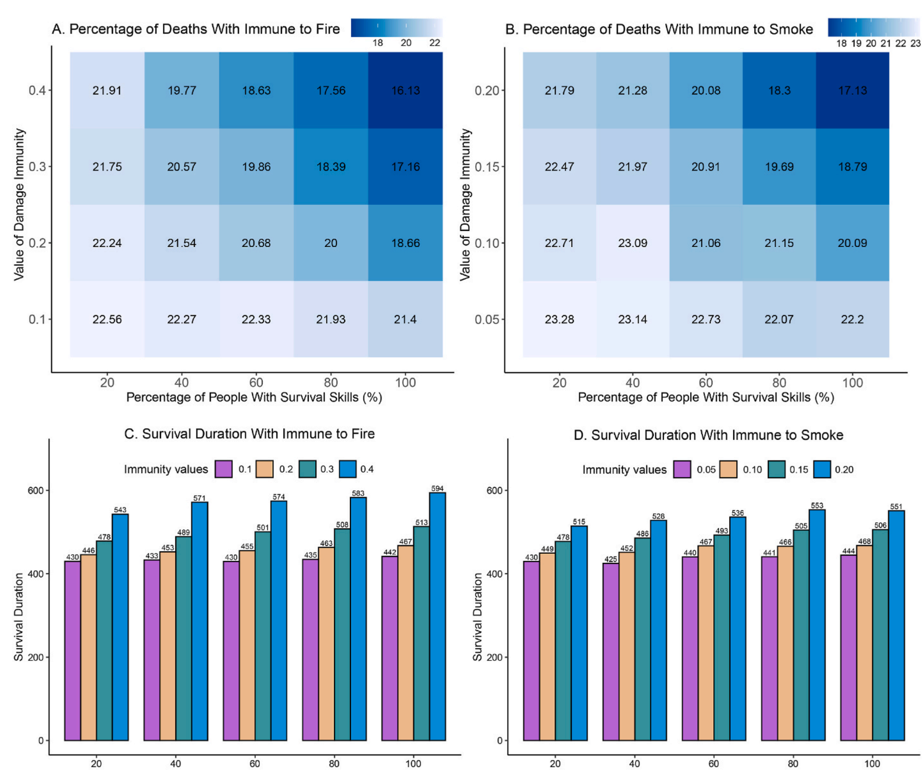

Fig. 7. The impact of survival skills on deaths and survival duration under single-damage immunity pattern. In Panels 7A & B, the x-axis represents the percentage of skilled residents, and the y-axis represents the values of damage immunity. The legend color represents the percentage of deaths. The numeric value represents the percentage of deaths and injuries in Panels 7A and B. In Panels 7C and D, the x-axis is the percentage of skilled residents, and the y-axis is the survival duration. In Panel 7C, different colors represent different immunities levels to fire damage. In Panel 7D, different colors represent different immunities levels to smoke damage.

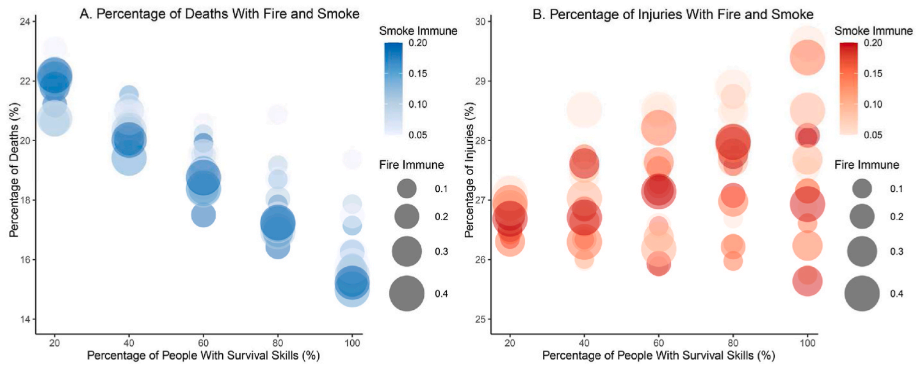

Fig. 8. The impacts of survival skills under dual-damage immunity pattern. The x-axis is the percentage of residents with skills, and the y-axis represents the percentage of deaths and injuries. In Panels A and B, the darker color indicates higher immunity to smoke damage, and the larger circle represents higher immunity to fire damage.

to achieve a long survival time, which is longer than the real case situation ($T \approx 420$ ticks). This results from residents' rational use of survival skills in a fire. In addition, survival skills may cause residents in the fire-immune pattern to achieve a longer survival time than in the smoke-immune pattern. This is because smoke damage is continuous and more difficult to prevent. Also, residents can avoid direct contact with flames by covering something wet. Thus, fire damage immunity has a more significant impact on results.

4.4. Dual-damage immunity pattern

In the previous section, we explored the impact of fire or smoke immunity on single survival skills. However, fire and smoke harm residents in a real fire evacuation. Similarly, residents with survival skills are immune to both fire and smoke. Therefore, in this section, we explore the effects of survival skills in the sample with two damaged immunities. The result shows that the dual-damage immunity pattern also has substantial effects on the outcomes:

(a) **Dual immunity reduces deaths (y_2) and increases injuries (y_3).** For the real targe case, the percentage of deaths is 23.89%, and the percentage of injuries is 25.26%. In Fig. 8, the percentage of simulated deaths is relatively lower, and the percentage of simulated injuries is higher than in the real case. The reason is that some deaths have been converted into injuries in our simulations. The survival skills ensured that agents (who could have died) might survive, even though they may be injured. The more residents with survival skills, the fewer deaths and more injuries we have, which is ideal for social safety. The higher the value of damage immunity, the fewer deaths and more injuries we finally have. The population with the highest damage immunity value

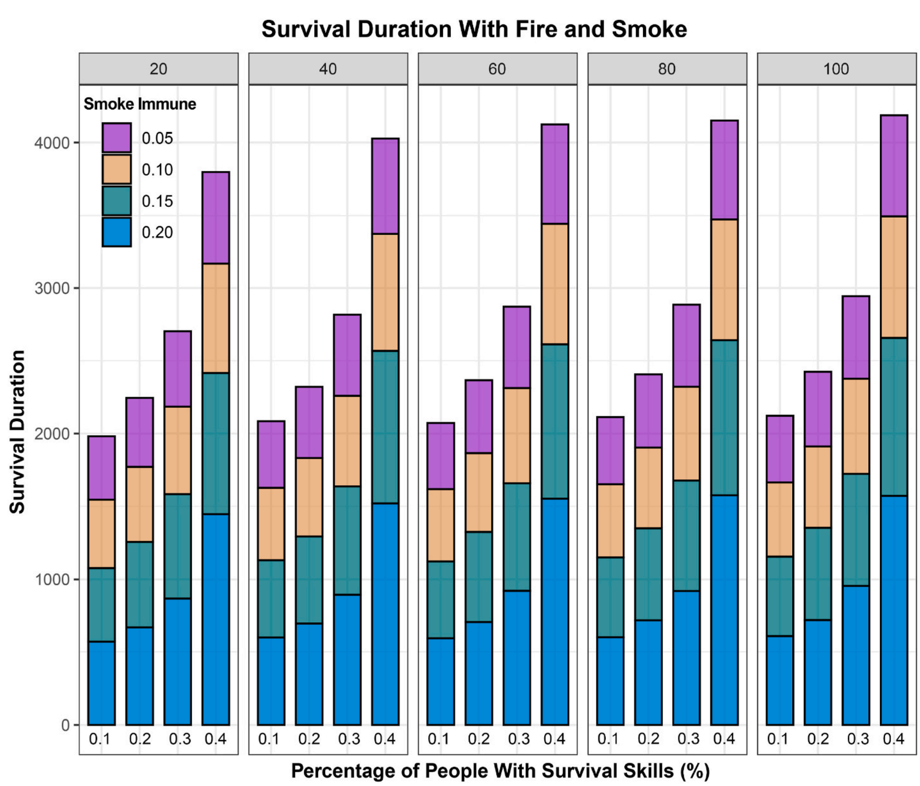

Fig. 9. The impact of survival skills in the dual-damage immunity pattern on the duration. The x-axis is the percentage of residents with skills, and the y-axis is the duration. Different colors represent the various immunities to smoke damage, and the different values (i.e., 0.1,0.2,0.3,0.4) at the bottom of the bar graph represent different immunities to fire damage.

does not necessarily have the lowest deaths or the highest injuries under the same percentage of skilled agents. The firing process is complex and dynamic, making it hard to calculate and simulate. One can achieve the desired goal of evacuation by mastering survival skills and achieving maximum values of injury immunity.

(b) **The dual-immunity skills will increase the survival duration (y_1) for all residents.** As Fig. 9 shows, the survival time (duration) increases when the number of residents with survival skills increases concerning survival time. In particular, when all residents have mastered survival skills, the survival time of the group increases significantly. Therefore, it shows that acquiring survival skills is crucial for residents in a fire, which can drastically increase the survival time of residents and the probability of successful evacuation. Regarding damage immunity, group survival time increases as residents become more proficient in survival skills. It suggests that appropriate defensive measures can reduce the damage caused by fire and smoke.

5. Verification of results' generalization

We validate and justify our findings' reliability by comparing other approaches' environmental settings and results. **First,** an environment comparison with other approaches is needed. The environment setting is a prerequisite for reliable findings. The commonly used method in fire dynamics is numerical simulation. A series of studies reconstructed the fire dynamic at Grenfell Tower, analyzing two fire spread phases consistent with our research (Guillaume et al., 2020). Other numerical simulations also set two phases of fire spread, including the initial vertical spread and the later horizontal spread. The time point of fire spread is consistent with our established setting. Moreover, other numerical models and computational fluid dynamics (CFD) indicate that fire and smoke are the main hazards in high-rise building fires (He et al., 2022). We establish reasonable fire spread and damage formulas based on existing research, as Equations (1) and (3) show. Many studies apply ABM to mimic rooms, corridors, and stairs to explore the evacuation process (Wang and Weng, 2014), demonstrating the ABM's wide applicability and rationality in high-rise building fires. Therefore, the environment settings, rules, and methods are reasonable and reliable. **Second,** results compared with other approaches will validate and justify the findings. Research on crowd evacuation in high-rise fires typically uses agent-based modeling, experimental or qualitative research. We compare the results from different method to validate our findings. Our findings include the effectiveness of alarm designs, social force evacuation, and fire and smoke injury. The alarm designs represent the effectiveness of fire information. The bespoke instructions can effectively reduce the delay-time of residents' response and the adverse impact of evacuation (Gerges et al., 2021), indicating the significance of the information. Our findings also determine the effectiveness of alarm information. Social force evacuation is an evacuation strategy. Other experimental research indicates that the person in front determines or limits the walking speed of residents behind him, which is called the platoon effect (Huo et al., 2016). Meanwhile, if some individuals move too quickly, it will slow down their overall speed, which shows the "faster is slower" effect (Lin et al., 2016). It explores the counterintuitive effect of evacuation speed, which aligns with our findings. At the same time, we propose an effective evacuation strategy based on our findings. For fire and smoke damage, smoke spreads faster than in simulation (Hostetter and Naser, 2022). If smoke damage can be prevented on time, the chances of survival will increase. This conclusion is similar to our findings, but we further explored the various impacts of smoke and fire damage on the percentage of deaths and injuries.

Our models do have generalization ability. **First**, agent-based modeling (ABM) has been proven reliable for providing mechanism-oriented explanations of phenomena. Agent-based modeling has a rich development history that spans multiple disciplines and decades. Since Schelling's segregation model in race and income (Bullinger et al., 2021), ABM has gained increasing acceptance and recognition in architecture and fire dynamics (Bankes, 2002). **Second**, the Grenfell Tower case has representativeness. Grenfell Tower is a typical high-rise fire case, and its structure is common in other high-rise buildings. Exploring the Grenfell Tower case also reveals the possible evolution of other similar structured high-rises. **Next**, we find similarities in some common phenomena by comparing the conclusions of other approaches. Based on existing research, we analyzed the role of information, the impact of different types of injuries and proposed new evacuation methods. Since the model is simplified and idealized, it is also somewhat highly abstract. Although our findings are based on one case, the results obtained from abstract models are somewhat generalizable. It will not change overall due to slight changes in specific parameters. For example, decreasing the number of floors or residents will not affect current findings. **Finally**, we conducted experiments on different floors and environments to demonstrate the generalization ability of the conclusion. If the number of floors or people undergoes alterations, and yet the research conclusion remains valid, it signifies that the conclusion possesses generalizability. This inference is supported by empirical evidence. We rebuilt a model with half the height ($floors = 12$) and half the number of residents ($N = 147$) to simulate the self-rescue process in a

Table 2
Parameter values of simulations.

Parameters		Group size (N)	Number of Floors	Survival Proportion and Values	Deaths (%)	Injuries (%)	Ticks
Alarm	True	100	12	\	10.32	12.31	\
	True	200	12	\	23.14	9.83	\
	True	300	12	\	29.83	9.46	\
	False	100	12	\	11.19	30.87	\
	False	200	12	\	23.25	24.85	\
	False	300	12	\	29.67	22.20	\
Evacuation strategies	Panicky	147	12	\	17.25	29.30	\
	Rational	147	12	\	4.16	34.45	\
Damage reduction	Fire	147	12	20 (0.2)	17.44	28.07	343.26
	Fire	147	12	60 (0.2)	16.33	29.17	366.49
	Fire	147	12	100 (0.2)	15.64	29.43	377.12
	Fire	147	12	20 (0.4)	16.83	26.00	465.89
	Fire	147	12	60 (0.4)	16.00	27.00	499.11
	Fire	147	12	100 (0.4)	15.57	27.41	511.94
	Smoke	147	12	20 (0.1)	17.16	27.21	340.53
	Smoke	147	12	60 (0.1)	16.94	27.90	361.40
	Smoke	147	12	100 (0.1)	16.02	28.52	365.58
	Smoke	147	12	20 (0.2)	17.10	27.53	394.60
	Smoke	147	12	60 (0.2)	16.14	28.23	417.43
	Smoke	147	12	100 (0.2)	15.44	29.50	423.44

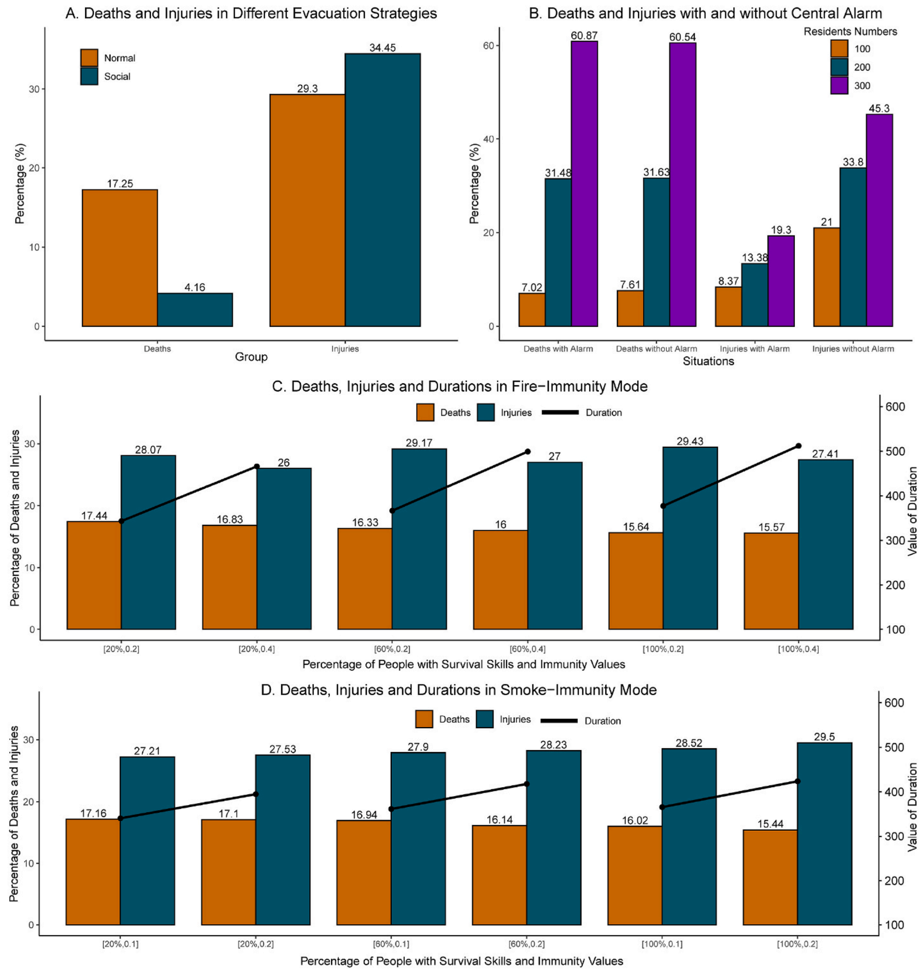

Fig. 10. Verification Experiments in different scenarios. Panel A shows the percentage of deaths and injuries for the normal and social-force evacuation in the stairways. Panel B shows the impact of fire with and without a central alarm. Panel C is the impact of survival skills on deaths, injuries & survival duration under the fire-immune pattern. Panel D is the impact of survival skills on deaths, injuries & survival duration under the smoke-immune pattern. The black line represents survival time (Duration).

fire. The specific parameters of the experimental simulation are shown in Table 2, and the specific results are output in the form of graphs in Fig. 10.

The conclusion regarding social force evacuation is consistent with our findings. We compare the two evacuation strategies in the same environmental settings. Fig. 10A shows that the percentage of deaths is substantially reduced, but the percentage of injuries increases under the social force model. Due to the social forces model, some people who may have perished in the fire were less likely to collide (suffer injuries) in stairways, allowing them to complete the evacuation more efficiently and survive. This conclusion is consistent with our findings. We also discuss the effect of the central alarm system. Fig. 10B indicates that the percentage of deaths and injuries gradually increased with increased group size. There is little difference in the percentage of deaths with or without the alarm. However, the percentage of injuries with the alarm is much lower than those without the alarm. This conclusion is consistent with our previous findings.

In the immunity pattern of single-damage, we select two types of immune values: moderate immunity (Fire=0.2 & Smoke=0.1) and higher immune values (Fire=0.4 & Smoke=0.2). In addition, we also set three classes of group size with survival skills: low (20%), moderate (60%), and high percentage of the population (100%). In the fire-immunity model, Fig. 10C shows that with the same group size, as immunity (immune values) increases, there is a slight decrease in the percentage of deaths and injuries and a substantial increase in survival time. Fig. 10D demonstrates that the situation in the smoke-immunity model is largely consistent with the findings of the fire-immunity model.

First, the percentage reduction of deaths is consistent with our findings. With lower floors, agents can perceive fires more quickly and take action, and the effect of skills proficiency is not as significant as high-rise fires. **Second**, the injury percentage is slightly lower. It is also related to the number of floors. The increased immunity and reduced percentage of deaths in high-rise fires come at the cost of increased injury rates. Agents who might have died survived with the help of survival skills, although they suffered different injury levels. The survival time of agents in both models increased substantially, which is consistent with our previous findings. Therefore, our findings can be generalized to evacuation plans for different cases.

6. Conclusions and discussions

With rapid urbanization and growing urban areas, high-rise building fires have posed significant public safety challenges (Alianto et al., 2022; Xing and Tang, 2012). We consider the self-rescue behavior of individuals to be the critical factor in evacuations. Agent-based modeling (ABM) is reliable for providing mechanism-oriented explanations of phenomena. Grenfell Tower is a typical high-rise fire case, and its building structure is also typical among other high-rises. Exploring the Grenfell Tower case also reveals the possible evolution of other similar structured high-rises. Taking the Grenfell Tower case as an example, we construct the 3D model and explore fire evacuation. We focus on agents' self-rescue skills and behaviors in high-rise building fires. Based on the simulated data, we obtained findings and discussions on central fire alarms, individual behaviors in the stairways, and survival skills in case of fire. Since the model is simplified and idealized, it is also highly abstract. Although our findings are based on one case, the results obtained from abstract models are generalizable. It will not change due to slight changes in specific parameters.

We have some findings that can guide individual behaviors and public response strategies: **(a) Central alarm system can reduce deaths and injuries.** First, the number of deaths & injuries is significantly lower if we have a central alarm system. This system allows residents to be alerted of fire and evacuate quickly. Second, as the crowd size increases, the impact of the central alarm system on deaths and injuries decreases. However, it is still better than the real case without this alarm system. Therefore, it is necessary to install central alarm systems in tall buildings. In addition, following the lessons of Grenfell Tower, the number of agents in high-rise buildings should not be increased excessively, and the density inside should be contained. **(b) Extended social force evacuation can avoid shoving and pushing, thereby reducing casualties.** We introduce the crowd shoving into the model to fit the real case. We also propose a practical strategy for evacuation by social force to avoid pushing and shoving in stairways under panic. The results confirm the effectiveness of our social force evacuation. Governments should apply the evacuation principles of the extended social force model to organize people for fire evacuation training. Residents who effectively master this evacuation skill can reduce unnecessary risks. **(c) Survival skills reduce deaths.** We can use survival skills to reduce social losses as much as possible. However, the impact of survival skills on smoke damage is limited, and the permanent damage caused by smoke cannot be prevented well. We should pay more attention to the smoke in the fire. Under the dual-damage immunity pattern, the number of deaths under each parameter combination is lower than in the real case. In addition, survival skills helped the group achieve fewer injuries and deaths in simulations. For survival duration, survival skills help individuals to survive longer. For each damage-immunity pattern, the simulated survival duration is higher than the real case, which increases the probability of successful escapes. Therefore, governments and communities should prepare more smoke masks in high-rise buildings. Meanwhile, each family should be well-prepared for emergencies, such as purchasing protective materials, learning self-rescue knowledge, and receiving BST training. **(d) Limitations and future works.** We construct a highly idealized model of crowd dynamics and human behaviors during the fire evacuation. The actual evacuation is more complex and has more responses, such as panic, collective irrationality, imitation, leader appearance, and external rescue factors. This mechanism has a different impact on fire evacuation. In further research, many assumptions and simplifications need to be improved to examine the interaction between people. Other significant factors should be introduced to the model, such as emotion, external firefighters, and concurrent disasters.

CRediT authorship contribution statement

Peng Lu: Conceptualization, Formal analysis, Writing – original draft. **Zhuo Zhang:** Data curation, Investigation, Validation. **Chiamaka Henrietta Onyebuchi:** Methodology. **Lifan Zheng:** Visualization, Software, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Social Science Foundation of China (Grant No. 19ZDA143 & 21ASH003), Wuhan East Lake High-Tech Development Zone (also known as the Optics Valley of China, or OVC) National Comprehensive Experimental Base for Governance of Intelligent Society Project, and the Fundamental Research Funds for the Central Universities of Central South University (Grant No. No.2023ZZTS0826 & No.CX20230127 & No.2023ZZTS0526).

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