Agent-Based Modeling Reveals Self-Rescue Behaviors and Optimized Fire Safety Measures in Factory Building Fires

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Abstract

Seeking help during a fire is challenging, highlighting the importance of individuals mastering self-rescue skills for effective evacuation. This paper discusses the fire at Kaixinda Trading Co. in Anyang, Henan Province, using it to validate an agent-based model that simulates behaviors during fire evacuations. The model incorporates percolation and social force theories, and its accuracy is confirmed by comparing simulated results with actual data on fire duration, deaths, and injuries. Simulation results suggest that self-rescue skills significantly reduce casualties, and functioning fire alarm systems further minimize losses. Additionally, integrating the social force model into evacuation strategies decreases the number of deaths and injuries compared to standard evacuation methods. This research offers practical insights for enhancing fire safety measures in steel structure factories, providing valuable recommendations for fire prevention and response strategies.

Key words: Crowd dynamics, Social force model, Self-rescue behaviors, Agent-Based Modeling

I. Introduction

The occurrence of fire accidents not only results in casualties and economic losses but also disrupts the normal social and production order. Particularly, in densely populated places such as hospitals, residential buildings, school dormitories, and office spaces, the presence of combustible materials, concentrated personnel, and large spaces often leads to severe consequences in the event of a fire. Since 2022, there have been multiple severe fire accidents in densely populated places. For instance, in November 2022, a fire at Kaixinda Trading Co., Ltd. in Anyang City, Henan Province, resulted in 42 deaths and 2 injuries. In April 2023, a fire at Changfeng Hospital in Fengtai District, Beijing, caused 29 deaths and 42 injuries. In January 2024, a fire in a street-front shop in Xinyu City, Jiangxi Province, resulted in 39 fatalities and 9 injuries. In the same month, a fire in a middle school dormitory in Nanyang City, Henan Province, resulted in 13 deaths and 4 injuries. Additionally, in February 2024, a fire in a residential building in Nanjing City caused 15 deaths and 44 injuries. Therefore, measures must be taken to mitigate the severe consequences of fires in densely populated places. Preventing fires requires attention to the preconditions for their occurrence, namely ignition sources, combustible materials, and oxidizers (oxygen), such as controlling combustible materials, isolating oxidizers, and eliminating ignition sources. However, focusing solely on the conditions for fire occurrence without addressing building materials, fire alarm systems, and evacuation strategies poses challenges in dealing with fires in densely populated places. This study will focus on evacuation models after the occurrence of a fire, which are crucial for reducing casualties caused by fires. Evacuations during fires in densely populated places are more complex and diverse. Additionally, toxic gases generated in the fire can cause indirect harm to individuals. Compared to other fire scenarios, fires in densely populated places have more potential fire hazards, spread rapidly, and pose a high risk of individuals being trapped. When a fire occurs, professional rescue forces (firefighters) may find it difficult to reach the scene promptly to rescue trapped individuals. Therefore, self-rescue behaviors during a fire are indispensable and should be considered the best personal choice. The continuous occurrence of fires in densely populated places constantly reminds us to focus more on self-rescue behaviors. This study aims to reveal the basic evacuation patterns in fires occurring in densely populated places through computational methods and, based on these patterns, to examine the impact of self-rescue behaviors on reducing fire losses.

The fire prevention measures and rescue strategies employed depend on several factors, such as the type and development trend of the fire, the location and environment where the fire occurs, and the human and material resources available at the scene of the fire. Research on fires in densely populated places primarily focuses on the following area: (1) Numerical simulation of fire dynamics. Fire dynamics primarily investigate the movement of fire smoke in open and confined spaces, as well as the mechanisms of toxic smoke release and its impacts on human health. A dynamic model of fire spread in large buildings, considering both horizontal and vertical directions of fire spread, was studied, proposing an algorithm for simulating the fire spread process and calculating the dynamic fire spread probability at each time step, with detailed fire spread calculations performed for a two-story office building (Cheng H et al., 2011). A liquid pyrolysis model was applied to the Fire Dynamics Simulator (FDS) to predict the combustion flux in multicomponent pool flames, validating the data with steady-state pool flames of ethanol-water, ethanol-isopropanol, and ethanol-hexane mixtures (Yip A et al., 2021). The basic principles of pool fires, including scale effects, wind effects, pressure and gravity effects, and multi-pool fire dynamics, were comprehensively reviewed, with a focus on the research conducted over the past decade on multiple pool fire incidents and their merging dynamics (Chen Y et al., 2023). The importance of local point measurements in wildfire experiments conducted in pine forests was demonstrated, through measurements of temperature, velocity, and radiant heat flux (Mueller E V et al., 2018). The behavior of smoke flow in six common smoke control systems during a high-rise residential fire was studied, finding that hot smoke could spread to upper indoor spaces through stairwells, and smoke entry into staircases and vertical transmission would be more challenging when stairwell pressures were high (Y Chen et al, 2015). Classic self-similar turbulent smoke plume theories were utilized to predict velocity, temperature, and concentration fields in large-scale turbulent smoke plumes and the Fire Dynamics Simulator (FDS) was used for numerical simulations of turbulent fires with various heat release rates in confined spaces (Ahn C S et al, 2019). Results from an experimental study aimed at exploring factors affecting the dynamics of fires in open compartments with exposed wooden ceilings were presented, proposing a scaled-down test method, comparing the observed fire behavior at a small scale with large-scale experiments reported in the literature (Nothard S et al, 2022). Fire Dynamics Simulator (FDS) software tools and computational fluid dynamics were used to reconstruct a fire scene in a long-term care facility on the seventh floor of a hospital in New Taipei City, Taiwan (Huang Y H et al, 2022). A fire scene was reconstructed using the latest version of the NIST Fire Dynamics Simulator (FDS) program based on official fire investigation reports and NFPA 921 guidelines, exploring a case of a hotel fire in Taiwan that resulted in severe casualties (Chi J H, 2013). The Fire Dynamics Simulator (FDS, version 4.0.5), particularly using parallel processing methods, was employed to simulate a hotel arson case in Taiwan (Shen T S et al, 2008).

(2) Fire Risk Assessment. A building fire risk analysis model based on scenario clusters and its application in building fire risk management were proposed (Xin J et al1 2013). The 1991 Beiglestone Fire Technology Award-winning paper "Fire Risk Analysis: A General Conceptual Framework for Descriptive Models" was revisited, with elaboration on changes in conducting fire risk analyses (Hall J R et al, 2010). The management of accidental residential fire risks was explored by developing a Geographic Information System (GIS) to support residential fire prevention, based on an 18-month case study by the UK Fire and Rescue Services (Taylor M J et al, 2011). An integrated fire station location model based on fire risk assessment was proposed, which assesses spatial location, land attributes, population density, floor area ratio, and fire incident indicators across different areas to determine fire rescue risk levels

and corresponding response times, establishing a target model to maximize fire response coverage (He Q et al, 2024). A case study of fire risk analysis for a six-story light-frame apartment building was introduced, aiming to demonstrate the performance of CU risk, especially the impact of wall barriers on building fire risks (Li X et al, 2016). A thorough analysis of the fire safety levels in London from 2009 to 2020 was conducted, including variations in fire safety levels across different types of residences and protection levels (Bonner M et al, 2024). The fire situation in China from 1991 to 2010 was analyzed, examining fire incident data over time, space, and causes from the past 6 years, revealing characteristics and factors influencing fire risks (Xin J et al, 2014). A Historical Fire Risk Index was proposed, utilizing a multi-attribute assessment linear additive model to measure relative fire risks (Watts Jr J M et al, 2001). The fire risk at a school for the blind was assessed using fire inspection checklists, brainstorming, and the Analytic Hierarchy Process (AHP) to estimate fire risks in the school's buildings (Ketsakorn A et al, 2023). A fire in a four-story building was simulated, selecting one wing (single fire compartment) for simulation, and the study explored the impacts of different design solutions on the overall building's fire risks (Björkman J et al, 1996). The differences in the perception of residential fire injury risks among the Swedish population were investigated, showing that risk perceptions vary due to socio-demographic factors (Mankell A et al, 2023). The FIREHARM (Fire Hazard and Risk Model), a research model for mapping fire hazards and risks, capable of calculating common measurements of fire behavior, hazards, and impacts to spatially depict fire hazards, was introduced (Keane R E et al, 2010). A method that uses U.S. housing, room layouts, and fire incident data, along with experimental heat release rates, material degradation rates, and thermal properties, combined with physical fire models to estimate community-level average residential fire losses was introduced (Anderson A et al, 2018). A study focused on 215 residential fires involving only a single fatality in their database, with 85 being smoking material fires, using odds ratio (OR) analysis to investigate the scale and relative importance of risk factors associated with SMF (Xiong L et al, 2019). Through the introduction of Allianz Insurance Company's (ARC) fire risk assessment system, fire-related data of Taiwanese factory buildings were collected and the fire loss amounts and severity for 32 real fire cases were validated (Jen-Hao C et al, 2020). Three fire risk assessment models based on statistical machine learning and optimized risk indices were proposed, using real investigation data from Korean fires to validate the proposed models and compare their performance with traditional models (Choi M Y, 2021).

(3) Evacuation Studies. The pre-evacuation behaviors of residents in a fire were investigated, and the relationship between resident characteristics, building features, fire characteristics, and human behavior was studied (Zhao C M et

al., 2010). A severely casualty-inducing hotel fire scene was reconstructed as a comprehensive evacuation test site. Forty out of fifty subjects were divided into six scenarios for an exit width test, measuring evacuation times through exits of 0.75 meters and 1.2 meters (Chi J H, 2011). The differences between traditional and shelter-in-place evacuations for people with disabilities encountering a fire in a museum were discussed using the Pathfinder evacuation simulation software (Hu J J et al., 2012). In response to the issue of smoke reducing the visibility of emergency signage at fire scenes, a smartphone-based voice-guided evacuation system (SVGES) was proposed, offering alternative evacuation routes for trapped civilians at fire scenes, and its effectiveness was demonstrated through experimental validation (Kuo T W et al., 2013). The Discrete Design Method (DDM) was proposed to reduce the simulation time and cost of fire emergency evacuation simulations and was applied to a subway station to study the effects of different factors on fire emergency evacuation (Yang P et al., 2014). The most commonly used modeling approaches to simulate human behavior in fires, representing the evacuation process during fires, were outlined (Ronchi E, 2015). Data from four evacuations at the same university library, including two pre-planned (unannounced) drills and two unplanned evacuations due to false alarms, were provided (Lovreglio R et al., 2016). Human evacuation behavior in a fire was simulated using particle swarm optimization algorithms, and the simulation results for multiple objectives versus a single objective, and the presence of leaders, were compared (Junaedi H et al., 2017). A virtual reality system was developed for simulating emergency evacuation in a fire (Zhang J F et al., 2018). A Virtual Reality-based Behavioral Skills Training (VR-BST) method was proposed for teaching basic fire safety behavioral skills (Çakiroğlu Ü et al., 2019). An immersive VR simulation game method was offered, using consumer-grade virtual reality (VR) devices to construct an escape route in a high-rise residential building to simulate human reactions before evacuation in emergency fire situations (Bourhim E L M et al., 2020). The crowd dynamics model of emergency evacuation from industrial buildings under fire spread was introduced, combining the social force model with fire dynamics to study evacuation processes under fire spread (Benseghir H et al., 2021). An innovative technology integration framework was proposed based on situational awareness principles using the Internet of Things (IoT), Building Information Modeling (BIM), Virtual Reality (VR), and Augmented Reality (AR) technologies, and the functionality of this framework was validated based on simulated fire scenarios (Chen H et al., 2022). However, studies based on mathematical and system dynamics models have overlooked social and human factors. AR/VR technologies are expensive, and the gap between virtual and real worlds remains significant, making it difficult to fully align individual experiences (Ding N et al., 2022). Overall, existing work has mainly focused on evacuation with little attention to micro-agent self-rescue behaviors. Moreover, existing research has not elucidated the mechanisms of interaction between macro phenomena and micro-individuals, that is, how emergent phenomena at the macro level are formed through interactions at the micro level, which is key to understanding group dynamics during the evacuation process (Daud N A M et al., 2022). A review of the development of Multi-Agent Modeling (MAM) over the past few years and a discussion on the current state of development of multi-agent approaches, including the history and development of multi-agent modeling, were provided (Daud N A M et al., 2022).

Throughout the studies, it has been observed that research on crowd behavior during fire evacuations based on two-dimensional models fails to accurately capture the characteristics of human behavior. To accurately reproduce the characteristics of crowd behavior and self-rescue actions during fire evacuations, this study proposes to use agent-based modeling (ABM) to simulate the fire evacuation process, employing NetLogo software to establish a three-dimensional model of human behavior during fire evacuation. Utilizing ABM modeling to simulate the fire evacuation process offers the following advantages: (1) Agent Behavior Rules and Interaction Mechanisms. ABM modeling can set agent behavior rules and interaction mechanisms, as well as interactions between agents and the environment, thereby simulating the dynamics of crowds during a fire evacuation. Simulations based on mathematical models and system dynamics of fire evacuation processes often overlook the interactions between agents and between agents and the environment (OM Zvereva, 2020). ABM modeling can address these shortcomings. (2) Heterogeneity and Asymmetry. Heterogeneity refers to differences or diversity among agents. Considering the real situations in fire evacuations, where individuals differ in information access and behavioral choices (Li D et al, 2015), previous studies often assume homogeneity and symmetry in calculations (Chattoe-Brown E, 2013; Ormerod P et al, 2006). Asymmetry refers to the imbalance in interactions among agents and between agents and the environment. Various factors influence individuals' behavior choices during fire evacuations, and these factors do not affect individuals equally. ABM modeling allows agents to possess multiple attributes, making their behavior more closely align with human real behavior, thus better describing the heterogeneity and asymmetry of individuals during fire evacuations. (3) Repeatability. In studies simulating fire evacuation processes, it is inevitable that the same model may produce different results (Stieler D et al, 2022). To ensure that the ABM model faithfully replicates the real fire evacuation process and to enhance the reliability of the simulation results, it is necessary to ensure that each simulation outcome is consistent with real fire situations (Devezer B, 2019), laying a solid foundation for the further application of the model. (4) Facilitating the Integration of Fire Knowledge. Researching fires requires the integration of knowledge from multiple disciplines, such as fire prevention materials, architectural design, fire dynamics, and fire warning systems. A vast amount of research related to fires has been accumulated, and how to effectively integrate previous research findings is a challenge. ABM modeling has a natural advantage in integrating related knowledge (Lee K C et al, 2012), which can further advance research related to fires.

II. Theoretical Discussions

1. Methods and materials

1.1 Agent-based modeling

Since its inception, agent-based modeling (ABM) has achieved significant results across multiple research domains. For example, ABM has been used to explain why populations with very similar sociodemographic characteristics sometimes display substantial differences in levels of ethnic mobilization during mobilization processes (Srbljinovic A et al., 2010). The applicability of ABM in integrated cancer biology research has been elucidated through the introduction of a multiscale tumor modeling platform, discussing the challenges and future directions of ABM in cancer research (Zhang L et al., 2011). A multiscale consumer market model has been developed using ABM to address specific business challenges (North M J et al., 2012). ABM based on fuzzy agents has been applied to the construction industry to simulate the motivation and performance of construction workers (Raoufi M et al., 2013). It has been noted that applying ABM can integrate various causal relationships into coherent causal mechanisms, aiding in understanding the mechanisms behind multilevel phenomena and thus establishing more complete causal explanations (Antosz P et al., 2014). The unique contribution of ABM to providing coherent social science predictions due to its capabilities and methodologies has been highlighted (Chattoe-Brown E, 2015). The applications of ABM in the public health domain, including infectious and non-infectious diseases, health behaviors, and social epidemiology, have been reviewed (Tracy M et al., 2016). ABM and Life Cycle Assessment (LCA) have been combined to focus on analyzing 18 cases of consumer systems, subsequently analyzed according to the four stages of the LCA international standards (Micolier A et al., 2017). ABM has been applied to analyze terrorist attacks and mass movements, revealing the exact impacts of key factors or mechanisms (Lu P et al., 2018). By establishing an agent-based model, the factors influencing the adoption of emerging recycling technologies have been studied (Farahbakhsh S et al., 2019). ABM has been integrated with Building Information Modeling (BIM), incorporating the characteristics of buildings and users, to simulate emergency evacuations (Beyaz C et al.). Hence, it is evident that ABM has a rich field of applications, and in fire-related research, ABM has gained increasing recognition among scholars (Young E et al., 2021). The fire dynamics in densely populated places can be considered a complex system. Generally, complex systems consist of multiple elements interacting nonlinearly, thereby producing the micro-macro effects of the complex system, such as fires and emergencies (Mei S et al., 2015). Applying the ABM method to simulate the fire process in densely populated places can fully reveal the nonlinear relationships among the elements at the fire scene, as well as the suddenness and complexity of the fire occurrence process (Kaur N et al., 2022). This paper uses the ABM method to model and predict fires in densely populated places, providing decision-making information for fire warning and evacuation processes. The model logic is shown in Figure 1.

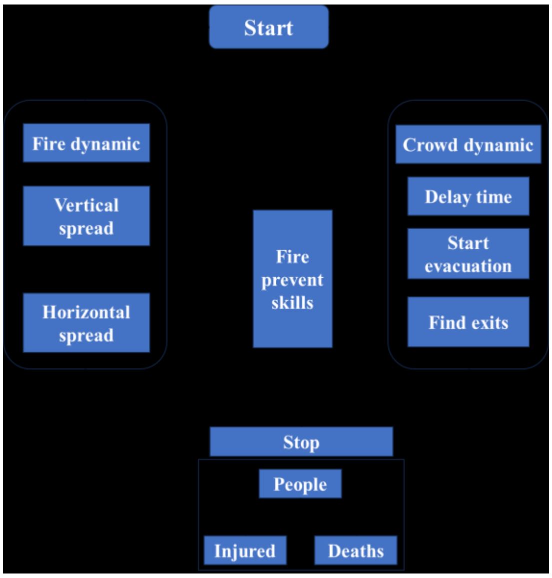

Figure 1 The logic of model

1.2 Real target case

This paper conducts an agent-based modeling (ABM) simulation of the fire at Kaixinda Trading Co., Ltd. in Anyang City, Henan Province, referred to hereafter as the Anyang Kaixinda fire. The incident was triggered by illegal and non-compliant welding operations by the company's leader, where high-temperature welding sparks fell onto a shelf, initially igniting the paper packaging of polyurethane foam sealant and ultimately leading to an explosion and combustion of the sealant. The building, a two-story steel structure, covers an area of 14,592 square meters and houses eight companies, with four on each floor. The selection of the Anyang Kaixinda fire as a case study is based on three reasons: (1) The fire resulted in severe consequences, including significant casualties and economic losses, while also having a profound impact on society. A review of the entire fire incident reveals multiple missed opportunities to mitigate losses both before and after the fire erupted, leading to extensive casualties. Investigating the underlying real reasons behind these missed opportunities is deemed crucial. (2) The fire scene is representative. The site of the Anyang Kaixinda fire is a typical two-story steel structure building, housing eight companies, isolated from each other by single-layer sheet metal. These types of buildings are prevalent due to their low cost and short construction period and are commonly used as office spaces or warehouses. Currently, there is a relative scarcity of simulation studies addressing fire evacuation processes in such buildings. (3) The scenario is suited to study self-rescue behaviors during the fire. At the time of the fire, there were 116 people inside the building; following the outbreak, 74 individuals successfully escaped, two were injured, and 42 died, with all casualties being employees of the same company, while employees from other companies managed to escape successfully. This study is not only interested in the potential relationships between building structure, fire safety design, fire alarm facilities, and the outcomes of the fire but is also keen on understanding the role of self-rescue behaviors in reducing casualties. This case provides ample support for the research presented in this paper, exploring how such behaviors could potentially save lives in similar future incidents.

This paper employs NetLogo to construct a virtual environment based on real-case data for the fire incident at Kaixinda Trading Co., Ltd. in Anyang City. (1) Fire Scene Layouts: As depicted below, Figure 2 illustrates the layout of the first floor, and Figure 3 illustrates the second floor, with the names of the companies represented by uppercase English letters. The fire originated on the first floor in Company A, with the majority of casualties being employees of Company H on the second floor. The fire affected an area of 11,000 square meters, destroying six companies. At the time of the fire, Company A lacked certain fire safety facilities, and the automatic fire alarm and sprinkler systems on the second floor were manually disabled, rendering them ineffective. This failure prevented Company H's employees from receiving timely fire alerts and evacuation instructions. Additionally, the absence of automatic fire alarm and sprinkler systems on the first floor allowed large volumes of high-temperature toxic smoke to quickly spread to the second floor via the stairways. By the time Company H's employees detected the fire hazard, dense smoke had rapidly filled the entire area, placing these employees in grave danger and ultimately leading to a tragic loss of 42 lives. This reconstruction of events serves to highlight critical failures in fire safety measures and emphasizes the urgent need for improved fire safety protocols in similar infrastructures.

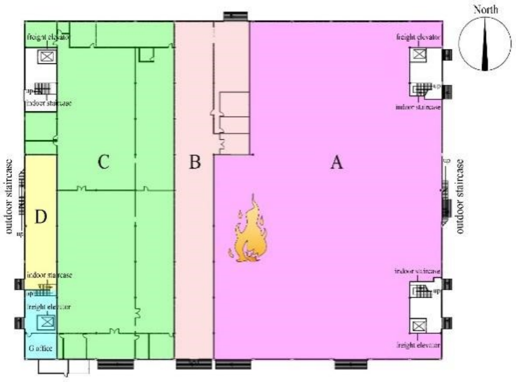

Figure 2 Distribution diagram of one layer

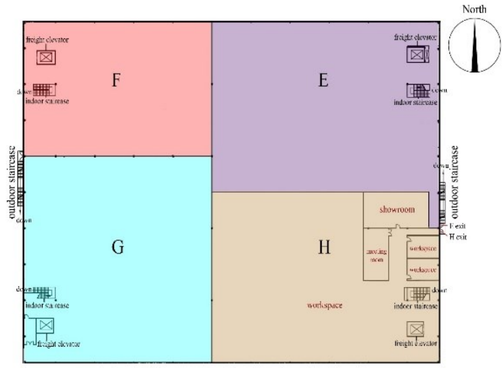

Figure 3 Second layer distribution diagram

(2) Fire Duration. On November 21, 2022, at 16:11, faint sparks began to appear at a welding operation point, followed by heavy smoke emanating from the site. By 16:12:28, the fire area had begun to burn intensely and rapidly spread. At 16:13, paper packaging ignited polyurethane foam sealants, causing splattering combustion and a multi-point burning state. At 16:18:45, personnel started evacuating, and by 16:21, the last evacuee had escaped. By 20:20, the fire was largely under control, with adjacent buildings effectively protected. At 23:40, all visible flames at the scene were extinguished, concluding a 7-hour ordeal. During the fire, 7 individuals in Company A's warehouse escaped, as did all 9 from Company C's warehouse, all 3 from Company D, all 26 from Company E, all 19 from Company G, and 10 from Company H. Although the entire fire lasted 7 hours, from the appearance of the first flames to the escape of the last employee, the effective time available for safe evacuation was only 10 minutes. (3) Fire Propagation Process. The fire propagation included both horizontal and vertical phases. At 16:11, the fire broke out on the shelves of Company A's warehouse, where a large amount of flammable material was stored. By 16:13, the fire rapidly transitioned from a single ignition point to multiple points, quickly evolving into a multi-point burning state and beginning to spread horizontally. Due to inadequately sealed staircases between the first and second floors, the fire swiftly ascended to the second floor. The building's overall steel frame structure, possessing a low fire resistance rating, partially collapsed under the intense heat. The resulting gaps provided new pathways for the fire to extend, thus accelerating its vertical spread to the upper floor. This describes the vertical progression of the fire. (4) Fire Damage Outcomes. When a fire occurs and begins to spread, if individuals can promptly perceive the risk, they are highly likely to successfully escape from the fire scene. During the Anyang Kaixinda Trade Co. fire, there was no organized evacuation, and the warehouse where the fire started lacked fire alarm systems, preventing others in the building from immediately recognizing the fire risk and consequently missing the optimal window for escape. This resulted in 42

fatalities, 2 injuries, and 74 successful escapes. Simulations based on Agent-Based Modeling (ABM) should align with the actual outcomes of the fire, taking into account factors such as risk perception during evacuation, evacuation behavior, and self-rescue skills. This study also integrates percolation theory (Beer T, 1990) and the social force evacuation model (Thalmann D et al, 2009). The last evacuee escaped at 16:21, with the first rescue team arriving at 16:31. Therefore, the ABM model used in this paper does not include firefighters. The research focuses on self-rescue behaviors during the evacuation process post-fire incident. The macroscopic pattern of self-rescue can be modeled through individual behaviors and interactions (Condorelli R, 2016). This approach allows for an examination of the heterogeneity of evacuees to reveal mechanisms of self-rescue behaviors.

1.3 Basic model settings

The basic setup of the ABM (Agent-Based Model) includes three components: the fire spread process, the scale and attributes of the agents, and the damages caused by fire and smoke, detailed as follows.

(1) Fire spread process

In the ABM modeling of the evacuation process for the Anyang Kaixinda Trade Co., Ltd. fire, the rate of fire spread is a crucial factor, which is related to the burning characteristics and spatial features of the fire scene (Cheng H et al, 2011). This paper refers to the settings of the fire spread rate established in the Fire Dynamics Simulator (FDS)-based fire spread model (Yi X et al, 2019) and simplifies it into equation (1) to simulate the fire's spread in both horizontal and vertical phases. In the equation, Q_f represents the area of fire spread, t_0 is the time when the fire started, t represents the duration of the fire, and α is the fire spread coefficient. In the case of the Anyang Kaixinda fire, the rates of fire spread in horizontal and vertical directions were not the same. In the initial stage of the fire, it took only about three minutes to escalate from the detection of smoke to vigorous burning. The presence of various flammable and combustible materials in the ignition area caused explosive combustion, accelerating the fire's spread throughout the storage area. Based on this, the horizontal fire spread rate α is set at 0.65. As the building is a two-story steel structure, and the precise rate of fire spread is challenging to determine, the model simplifies it to a uniform rate. Considering the fire started inside the building, the rate of fire spread was not influenced by external factors (wind, windows, and firefighting efforts).

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

(2) Scale and Attributes of Agents

During the fire, the building housed 116 individuals distributed across various company warehouses: 7 in Company A, 9 in Company C, 3 in Company D, 26 in Company E, 19 in Company G, and 52 in Company H. Consequently, the model is configured with an equivalent number of agents or persons $(N = 116)$. In modeling the evacuation process during a fire, the health status of individuals is crucial. This paper utilizes the health status indicator $Blood_i^t$ to reflect the dynamic health condition of each heterogeneous agent (i) at any given moment (t) throughout the evacuation process. Based on the results of the 2020 seventh population census, age distribution was chosen to simulate the health conditions of individuals during a fire evacuation. Since age approximately follows a normal distribution, the initial level ($Blood_i^0$) is set using formula (2), with a mean of 100 and a standard deviation of 20, to reflect this distribution.

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

(3) Damage Caused by Fire and Smoke

The damages caused by flame combustion and smoke in fires are difficult to quantify. This paper calculates based on actual case outcomes, where most survivors escaped within the first 10 minutes after the fire outbreak, and the last survivor successfully fled at 16:21. Therefore, the escape time of the last survivor is considered as $T = \max(t)$, which is $T = 10$ minutes. The impact of high-temperature toxic smoke on trapped individuals is evaluated by calculating the concentration of carboxyhemoglobin in the blood. In this study, smoke damage $Smoke_{Dam}$ is set at 0.22, representing the amount of blood loss per minute. Additionally, during the evacuation, the environmental temperature at the fire scene significantly increases, causing burns to trapped individuals' bodies and damaging their skin and respiratory tracts, which in turn affects the mobility of evacuating personnel. Fire injuries are calculated according to equation (3), where $Fire_{Dam}$ represents the damage caused by the fire in a short period (0-1 minute) and $T_{average}$ is the average temperature around an individual in that time frame. During the Anyang Kaixinda fire, the peak temperature exceeded 1400°C, with an average temperature of 500°C. In the model established in this paper, the damage caused by the fire is quantified as a blood loss rate of 0.3 per minute.

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

1.4 Self-rescue behavior settings

Self-rescue refers to the actions taken by individuals in emergency situations to extricate themselves from danger (Bris R et al., 2009). Previous research on self-rescue has focused on the spatial transition from hazardous areas to safe zones (Liang W et al., 2022). Unlike prior studies, this research provides a detailed description of the micro-behaviors of agents within the model, such as the perception of fire information, the influence of social forces, and the capacity of survival skills to mitigate fire-related injuries.

(1) Evacuation Speed

After the onset of the fire, self-rescue behavior involves quickly evacuating from the fire scene. The building where the fire occurred has two floors; individuals on the first floor only need to move horizontally and are less affected by the high-temperature toxic smoke from the fire. Therefore, this study sets their horizontal movement speed between 0.5 to 1 meter per minute. Individuals on the second floor must first move horizontally to the staircase before proceeding vertically. Previous research indicates that horizontal movement speed is approximately 2 to 3 times faster than vertical movement speed (Ding N et al., 2021). As the actual vertical movement speed during the fire is unknown, this paper uses the average evacuation time (3 minutes) to calculate the vertical movement speed, setting it at 0.35 meters per minute in the model.

(2) Delay Time

Delay time is one of the critical factors affecting individual self-rescue behavior. Upon the occurrence of a fire, whether an individual can perceive the fire immediately and make a rapid and accurate judgment based on the actual situation is crucial for successfully escaping the fire scene. In the Anyang Kaixinda fire, because the first floor lacked fire alarm facilities and the second floor's fire alarm system was manually deactivated, workers on the second floor were unable to perceive the fire immediately, losing the optimal opportunity to escape. This study incorporates a delay time mechanism in the model to reflect the impact of delay time on evacuation, as detailed in equation (4). Delay time consists of two parts: perception time $T_{Perceive}$ and decision time $T_{Decision}$. Perception time refers to the time it takes for an individual to receive information about the fire in situations where automatic alarm systems are ineffective or absent. After the fire breaks out, individuals typically experience panic; mild panic can aid in quick decision-making, whereas excessive panic can impair an individual's decision-making and physical abilities (Shang et al., 2023). In the model established in this paper, it is assumed that the level of panic is related to the timing of fire perception: the earlier the fire is perceived, the milder the panic, which is more conducive to escape; the later the fire is detected, the greater the individual's panic, which is less conducive to escape, thus leading to an increase in delay time. This period is defined as the decision time $T_{Decision}$. In equation (4), the delay time T_{Delay} is composed of two parts: perception time $T_{Perceive}$, which occurs simultaneously with horizontal propagation, and decision time T_Decision, which is related to the floor on which the agent is located. Perception time is set as a random number between 0 and 35, and decision time $T_{Decision}$ is associated with the agent's floor.

$$T_{delay} = T_{perceive} + T_{decision} \qquad (4)$$

(3) Stair Behavior

In the Anyang Kaixinda fire, individuals on the second floor needed to evacuate through either indoor or outdoor staircases. Due to the limited space in staircases and the influence of dense smoke and fire conditions, inevitable crowding and shoving occurred, potentially leading to trampling and resultant casualties. This evacuation process is defined as the Normal Evacuation Mode in this paper. Beyond the normal mode, the Extended Social Force Model can also be used to simulate stair behavior during evacuation, which this study defines as the Social Force Evacuation Mode. The social force model is a discrete model in pedestrian dynamics (Sticco et al., 2021) that has been extensively expanded and refined (Han et al., 2017) to incorporate both social and physical factors during evacuation, reflecting the subjective consciousness of the crowd in real evacuation processes (Lu et al., 2021). The social force model is applicable to a variety of evacuation scenarios, such as evacuations on tilting cruise ships (Fang et al., 2022), subway stations (Wan et al., 2014), earthquake evacuations (Li et al., 2015), and crowd evacuations during terrorist attacks (Liu et al., 2018). Previous studies using the social force model for evacuation simulations often overlooked changes in individual speeds when using staircases (Wang et al., 2014). This paper employs four types of social forces to simulate individual stair behavior $(\overrightarrow{F_1}, \overrightarrow{F_2}, \overrightarrow{F_3}, F_4)$, as calculated in equation (5). Here, $\overrightarrow{F_1}$ represents the cohering force, which drives agents to move towards the group, forming clusters; $\overrightarrow{F_2}$ is the navigational force, calculating the vector direction between the crowd and the exit; $\overrightarrow{F_3}$ is the separating force, calculating the distance between individuals to avoid crowding and shoving when descending stairs. Unlike movement on flat surfaces, stair descent is influenced by forward speed, gravitational acceleration, and the landing surface of the stairs. Controlling one's speed is crucial to avoid collisions and trampling. F_4 represents a non-vectorial social force used to compute the average moving speed of the crowd. The three vector forces $(\overrightarrow{F_1}, \overrightarrow{F_2}, \overrightarrow{F_3})$ determine the direction of individual movement, while the non-vectorial force F_4 establishes the average speed of the crowd. As illustrated in Figures 4 and 5,

$(\overrightarrow{F_1}, \overrightarrow{F_2}, \overrightarrow{F_3}, F_4)$ jointly determine the mode of individual transfer in stair spaces. Based on this, the study compares the outcomes of Normal Evacuation Mode and Social Force Evacuation Mode.

$$\overrightarrow{F_1} = \left(\overrightarrow{A_0} - \frac{\sum_{i=1}^{N_1} \overrightarrow{A_\iota}}{N}\right), \overrightarrow{F_\iota} = \overrightarrow{\theta_0}, \overrightarrow{F_3} = \sum_{i=1}^{N_1} \frac{1}{\left(\overrightarrow{A_0} - \overrightarrow{A_\iota}\right)}, F_4 = \frac{dv_i(t)}{dt} = \frac{1}{i} * \sum_{i=1}^{N_1} (v_i - v_0) \qquad (5)$$

Figure4 Normal evacuation pattern

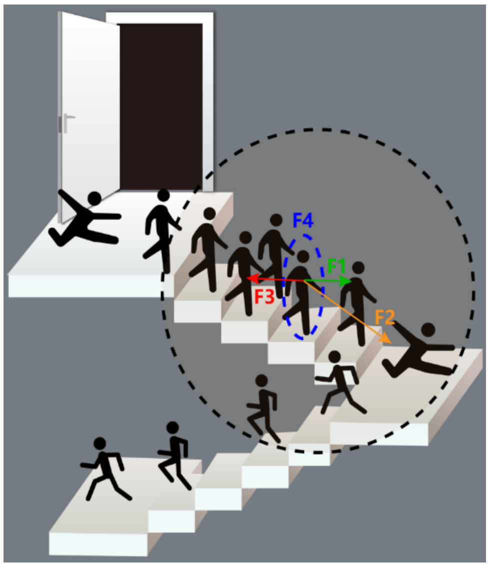

Figure 5 Social force evacuation

(4) Health Status and Self-Rescue Skills

During a fire evacuation, an individual's health status and self-rescue skills significantly influence their ability to successfully escape from the fire scene. This study utilizes equation (6) to assess an individual's health status, where $Blood_i^t$ represents the dynamic health status of agent i at time t, and $Blood_i^0$ indicates the initial blood value, which follows a normal distribution. $\sum_0^t Smoke_{Dam}$ represents the cumulative value of smoke damage from the start time to time t, and $\sum_0^t Flame_{Dam}$ represents the cumulative value of flame damage; individuals will suffer flame damage if they are within 1 meter of the fire source. Survival skills (λ) can reduce the damage caused by flames and smoke to the individual. According to equation (6), an agent is considered deceased when their blood value drops to zero. If the blood value falls below 60% of the initial value, the agent is considered injured. In severe fire scenarios, agents can reduce damage from flames and smoke through survival skills. In real cases, most employees are either unaware of fire self-rescue skills or unable to use them correctly. In this study, the survival skill coefficient is set as the λ term, allowing agents in the model to use survival skills to mitigate the damage caused by flames and smoke. The range of immunity coefficients for flame damage is $\{0.1, 0.2, 0.3, 0.4\}$, and for smoke damage is $\{0.05, 0.1, 0.15, 0.2\}$.

$$Blood_i^t = Blood_i^0 - \left(\sum_0^t Smoke_{Dam} + \sum_0^t Flame_{Dam} - \lambda\right)$$

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

(5) Injury Model

There are two primary injury models in fires: the Single Injury Model and the Dual Injury Model. The Single Injury Model refers to individuals sustaining injuries from either flames or smoke alone, whereas the Dual Injury Model involves individuals simultaneously suffering from both flames and smoke. In the Fire Immunity Mode, individuals will continuously suffer from smoke damage during evacuation, and based on their self-rescue capabilities (survival skills), they can achieve varying degrees of fire immunity, such as $\lambda \in \{0.1, 0.2,0.3,0.4\}$. For the Smoke Immunity Mode, individuals will suffer flame damage if they are within 1 meter of the fire source. Considering individual heterogeneity, different individuals are suited to varying degrees of smoke damage immunity, such as $\lambda \in \{0.1, 0.2,0.3,0.4\}$. Furthermore, in the Dual Injury Immunity Mode, different individuals exhibit varying levels of immunity to both fire and smoke, for instance, fire immunity $\lambda \in \{0.1, 0.2,0.3,0.4\}$ and smoke immunity $\lambda \in \{0.1, 0.2,0.3,0.4\}$.

Table1 Parameter values of simulations

Parameters		Interpretations	Initial Value	Value Ranges
Group size(N)		The number of employees	116	{100,150,200,250,300,400}
$Blood_i^0$		The initial blood distribution	$Blood_i^0 \sim N(100, 20^2)$	$Blood_i^0 \sim N(100, 20^2)$
$Blood_i^t$		The value of blood in t	/	$[0, Blood_i^0]$
The speed of agents(v)	Horizontal (v_{Hor})	The horizontal speed	$0.5 + s(0,0.5) m/min$	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)	0.3	0.3
	Smoke ($Smoke_{Dam}$	Blood loss (Inhalation)	0.22	0.25
Damage	Pusher	Blood loss	0.1	0.1
	Pushed	Blood loss	0.2	0.2
Alarm	True	Simulation (With Automatic fire alarm system)	/	Information homogeneity
	False	Reality (Without)	/	Information heterogeneity
Evacuation	Panicky	Reality (pushing and	/	Blood loss and location

strategies		shoving)		change
	Rational	Sim (No pushing or shoving)	/	/
Survival skills		Percentage of skilled agents	0%	$\{20\%, 40\%, \cdots, 100\%\}$
Damage reduction	Fire	Reduce damage from fire	0.00	$\{0.1,0.2,0.3,0.4\}$
	Smoke	Reduce damage from smoke	0.00	$\{0.05,0.1,0.15,0.2\}$

III. Optimal solution outcomes

1. Best-fitting solution

To validate the model's effectiveness and robustness, it is necessary to compare the simulation results of the model with the outcomes of the real case. This paper uses NetLogo to construct a simulation model. The building involved in the fire is a two-story steel frame structure workshop with 116 employees inside at the time of the fire. To ensure the realism and reliability of the model simulation, the simulation should match the key data of the real target case as closely as possible. This study selected three key data points: y_1(total duration), y_2(number of deaths), and y_3 (number of injuries). Based on the range of values for all parameters in Table 1, all parameter combinations are iterated during the simulation process to obtain the optimal solution, with each combination being simulated 200 times to achieve the most robust results. Based on the outcome data of the real case, the real case function is defined as $f_{real(\bullet)} = Y_i = \{10,42,2\}$, and the corresponding simulation function based on model simulation results is $f_{sim}(\bullet) = \{\hat{y}_1, \hat{y}_2, \hat{y}_3\}$. Equation (7) is used in this paper to calculate the difference (Δ) between the simulation function and the real case function. With the minimum difference (Δ), the best-fitting parameter value combination can be solved, which can be regarded as the optimal solution $Par^*(\bullet)$.

$$Par^*(\bullet) = ArgMin(\Delta) = ArgMin[f_{sim}(\bullet) - f_{real}(\bullet)]$$
$$= ArgMin\left(\sqrt{\frac{\Sigma(\hat{y}_1-600)^2}{200}} + \sqrt{\frac{\Sigma(\hat{y}_2-42)^2}{200}} + \sqrt{\frac{\Sigma(\hat{y}_3-2)^2}{200}}\right) \quad (7)$$

2.Validity and robustness supported

This paper employs two criteria, validity and robustness, to verify the optimal solutions of the simulation results. Validity requires that the simulation results accurately match the real target case, such as duration (y_1), number of deaths (y_2), and number of injuries (y_3). Robustness demands that the fit of the model simulation results should be stable and most probable, meaning the distribution of 200 simulation results (N=200) should form a bell-shaped curve, symmetric around the mean, and as close as possible to the real target case.

(1) Robust Fitting of Duration (y_1). The fire at Anyang Kaixinda Trading Co., Ltd. lasted a total of 7 hours, but

from the onset of the fire to the successful escape of the last employee, it was only 10 minutes (600 seconds). Consequently, this paper benchmarks the simulation of duration to 10 minutes (600 seconds). In the NetLogo simulation process, one second is taken as one time step (ticks) in the model simulation. The mean duration of the fire simulation is $\hat{y}_1 = 597.57 \approx 600$ time steps, roughly equivalent to the real target case of $y_1 = 600$ seconds (10 minutes). This indicates that our optimal solution $Par^*(\bullet)$ meets the validity criteria. The duration of 200 simulations was grouped and analyzed, as shown in Figure 6, where the duration (y_1) of the 200 simulations approximately follows a normal distribution, with a mean of 597.57 and a standard deviation (SD) of 36.16 (N=200), significantly smaller than the mean, indicating a concentrated distribution of data. Additionally, most data points lie close to the 45-degree line on the Q-Q normal probability plot. Thus, the validity and robustness of $Par^*(\bullet)$ regarding the duration (y_1) are well-supported.

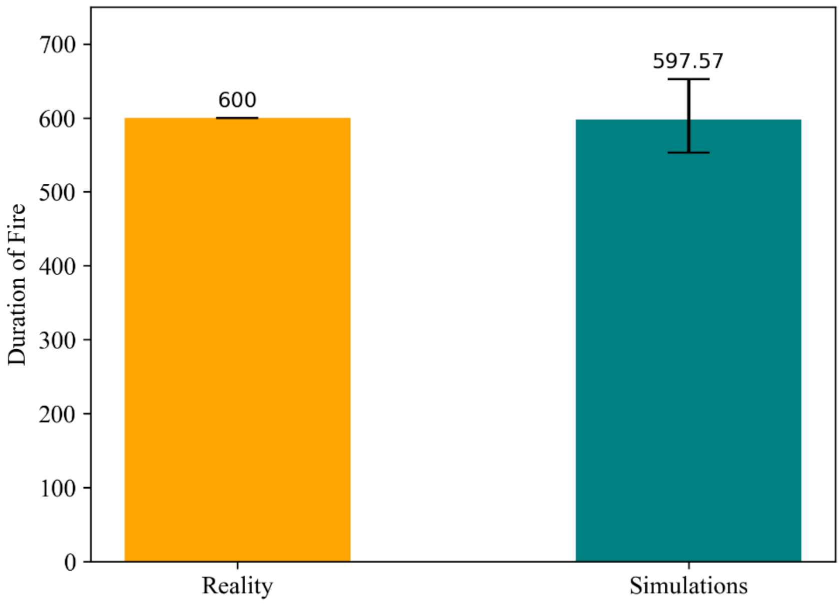

Figure 6 Reality and Simulations in Duration(y_1)

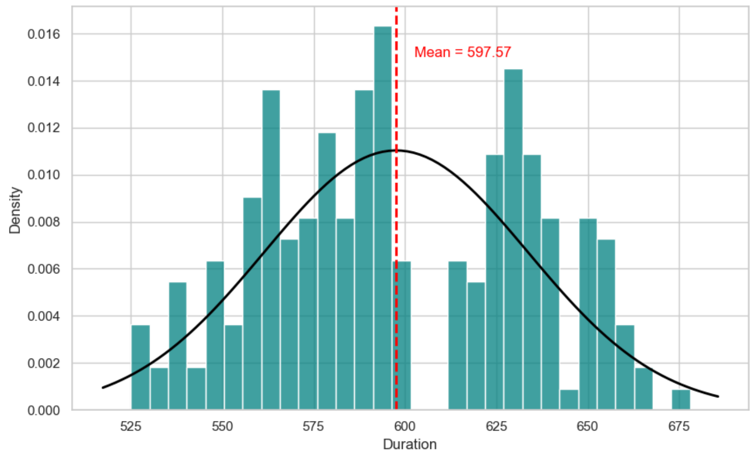

Figure 7 Density Distribution in 200 Simulations

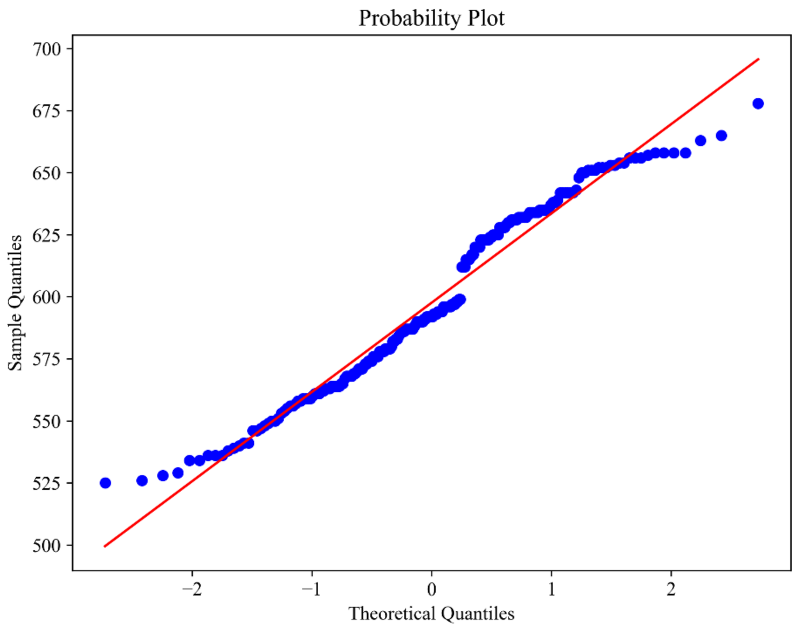

Figure 8 Sample Data Q-Q Normal Probability Plot

(2) Robust Fitting of the Number of Deaths(y_2) and Injuries(y_3). The Anyang Kaixinda fire resulted in 42 deaths (y_2) and 2 injuries(y_3), both of which were accurately and robustly fitted. As shown in Figure 9, the mean value for deaths is $\hat{y}_2 = 41.01(N = 200)$, approximately equal to the real target case number (y_2=42). The standard deviation (SD) of 200 repeated simulations is 12.39, significantly less than the mean (41.01), thus supporting the validity of the simulated number of deaths. To test robustness, the violin plot in Figure 9 indicates that most sample

data points fall within the normal range, supporting the robustness of the simulations. In Figure 10, the average number of injuries is $\hat{y}_3 = 2.48(N = 200)$, roughly equivalent to the real target case number (y_3=2). Moreover, the violin plot in Figure 10 shows that most sample data points are within the normal range. Thus, under 200 repeated simulations, $Par^*(\bullet)$ both demonstrates the validity of the simulation results and the robustness in fitting the real case results for the number of deaths and injuries.

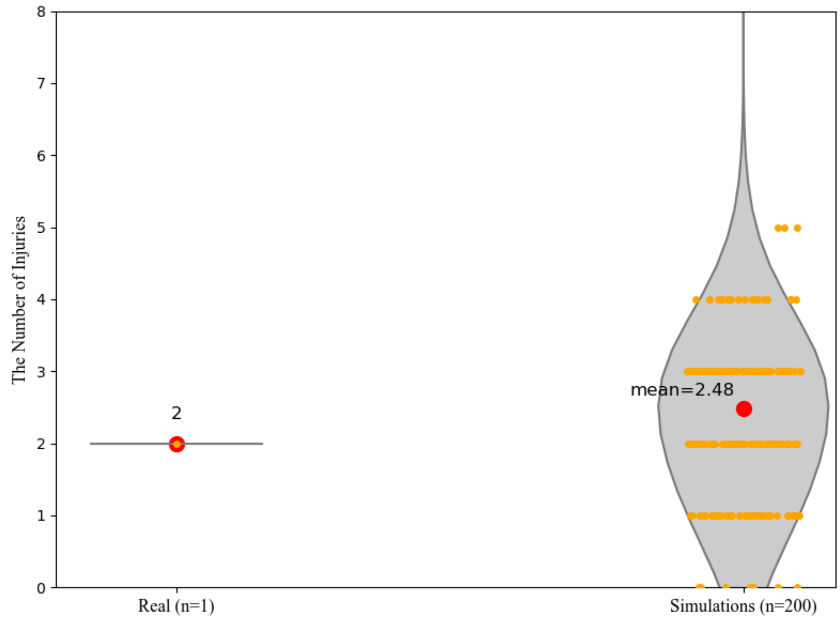

Figure 9 Fitting the Number of Deaths (y_2)

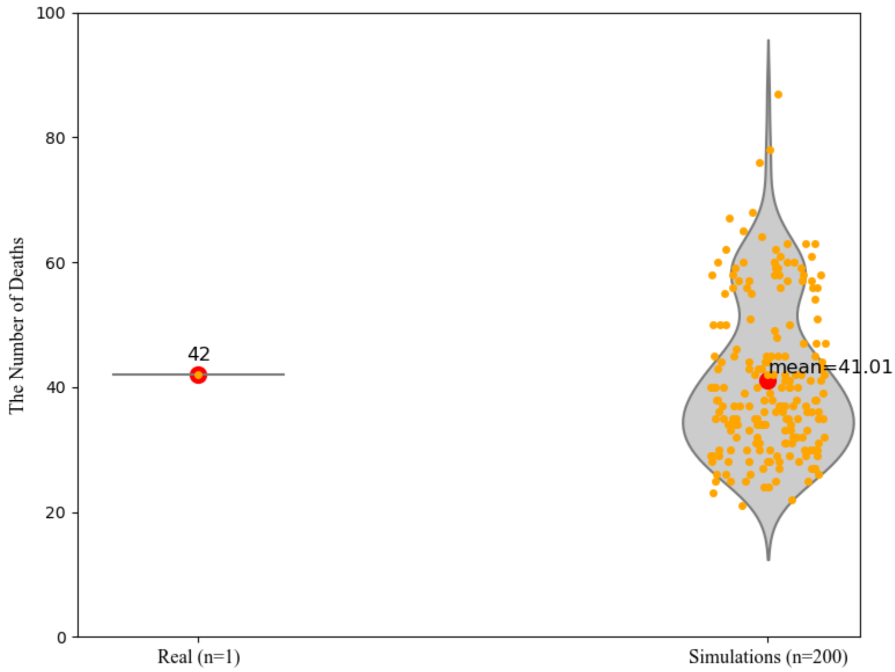

Figure10 Fitting the Number of Injuries (y_3)

4. Counterfactual experiments

Considering the validity and robustness of the optimal solution, it is evident that it has significantly captured the behavioral patterns of individuals and groups during the real fire evacuation process. Based on the optimal solution $Par^{*}(\bullet)$, the study iterates over the other parameters listed in Table 1 to obtain counterfactual outcomes. As in previous sections, each combination is simulated 200 times to achieve robust results for $\hat{y}_1$, $\hat{y}_2$, and $\hat{y}_3$. This methodology ensures that the simulated scenarios thoroughly represent the dynamics and variations observed in actual fire evacuation processes, thereby enhancing the reliability of the research findings.

3.1 The impact of automatic fire alarm system

In the Anyang Kaixinda fire incident, the first-floor warehouse where the fire started lacked an automatic fire alarm system, and the system on the second floor was manually disabled, resulting in the staff on the second floor not being promptly alerted about the fire, which led to severe consequences. This study examines whether the operational status of the fire alarm system at the time of the fire could have significantly reduced the number of casualties. To address this question, the paper compares the real situation (absence of a functional fire alarm system) with a counterfactual scenario (presence of a functional fire alarm system). The simulation results are presented below, offering insights into the potential impact of functional alarm systems on reducing fatalities and injuries during fires.

(1) The fire automatic alarm system can significantly reduce the number of deaths(y_2). According to legal and regulatory requirements, crucial locations should be equipped with fire automatic alarm systems. When the fire alarm system is operational, individuals' ability to perceive fire hazards increases significantly, providing more time for response and shortening evacuation delays, thereby enhancing the chances of successfully escaping the fire scene. As shown in Figure 11, under different group sizes, the death percentage with an operational fire alarm system is consistently lower than without one. As the group size increases, the death percentage also rises. For a group size of 100 individuals, the death percentage without a fire alarm system is 16%, while it is only 7% when the fire alarm system is operational. In contrast, when the group size increases to 300, the death percentage without a fire alarm system is 44.1%, compared to 22.3% with an operational system. However, when the group size reaches 400, the death percentages with and without a fire alarm system show no significant difference. This is because the building's steel frame structure may collapse after a period during the fire, deforming the indoor staircases used for escape, making them unsuitable for evacuation. Consequently, when the group size reaches a certain level, the evacuation time increases, thereby exacerbating the fire risk for employees still inside the building and leading to severe consequences.

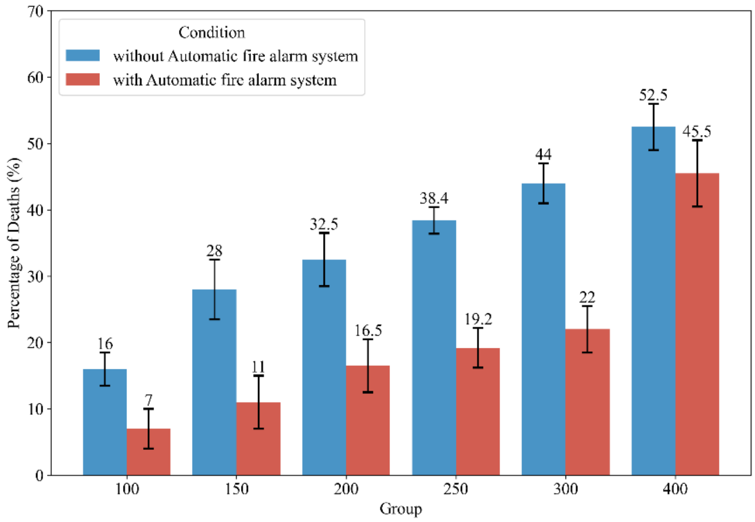

Figure11 Percentage of Deaths with and without Automatic Fire Alarm System

(2) When the fire automatic alarm system is operational, the number of injuries (y_3) also significantly decreases. As shown in Figure 12, for a group size of 100 individuals, there are 7 injuries when there is no fire alarm system, whereas no injuries occur when the fire alarm system is functioning. When the group size increases to 400, the injury percentage is 22% without a fire alarm system, compared to only 16% when the fire alarm system is operational. These results indicate that the injury percentage slightly increases with the group size, but the difference in injury percentages between different group sizes gradually narrows. The simulation results demonstrate that with an operational fire automatic alarm system, both the percentage of deaths and injuries significantly decrease as the group size increases, with the reduction in injury percentage being particularly notable. However, as the group size continues to increase, the effectiveness of the fire alarm system diminishes.

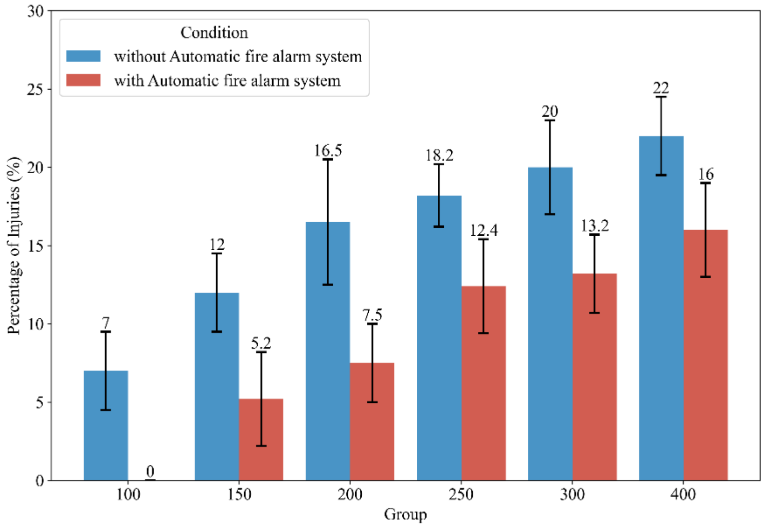

Figure12 Percentage of Injuries with and without Automatic Fire Alarm System

3.2 Evacuation strategy simulation

During the evacuation process in a fire incident, the chosen evacuation strategy is a crucial factor affecting the likelihood of successful escape. In a typical fire evacuation scenario, due to the panic among evacuees, crowding and pushing are inevitable, particularly noticeable during stairway evacuations. This paper simulates two types of crowd evacuation strategies: the first is a normal evacuation, where individuals start searching for escape routes as soon as they perceive the fire; the second is a social force evacuation strategy, which considers the combined effect of various "social forces" experienced by individuals during the evacuation to predict and plan evacuation routes, thereby achieving an efficient and orderly evacuation. The paper compares the death outcomes under these two evacuation strategies and differentiates the scenarios with and without operational fire automatic alarm systems.

(1) Compared to the normal evacuation strategy, the application of the social force evacuation strategy significantly reduces the number of deaths (y_2). As shown in Figure 13, for the real target case (without fire automatic alarm systems), the mortality rate can be significantly reduced, with one of the primary causes of 42 deaths in the real case being the failure to find correct evacuation paths. The percentage shown in Figure 13 is 25.49% (SD=9.98), which has been reduced to 15.97% (SD=9.05%) in Figure 14. Thus, these two values show a statistically significant difference. For the counterfactual case (with fire automatic alarm systems), the percentage is 18.73% (SD=7.30%), reduced to 7.92% (SD=3.36%) in Figure 14. Again, these two values show a statistically significant difference. Therefore, we

have two findings: the mortality rate can be reduced if agents use the social force model during fire evacuation. This model is robust whether or not a central alarm system is installed in this high-rise building. Figure 14 validates the effectiveness of evacuation under the social force strategy. In practice, the social force model can be enhanced through training, which governments, companies, or institutions can organize effectively.

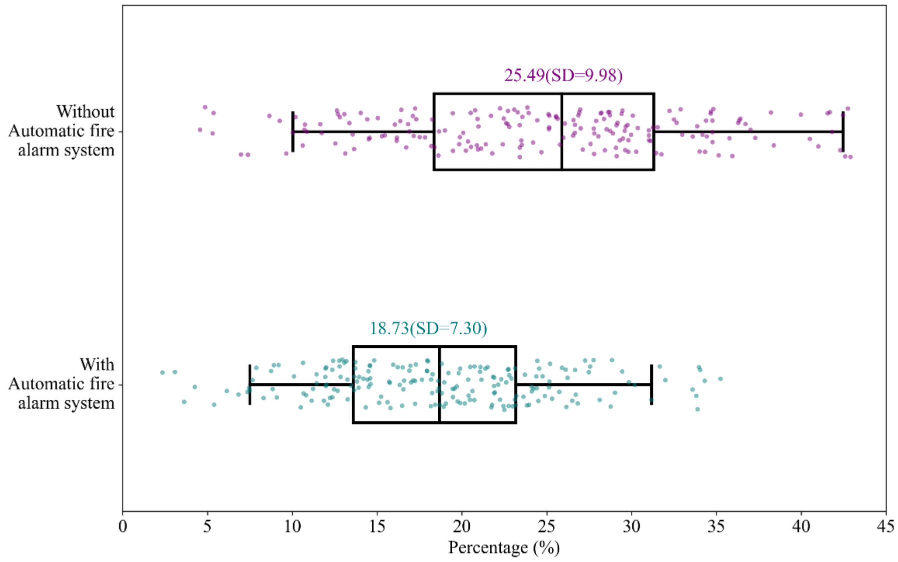

Figure13 The Percentage of Death in Normal Evacuation

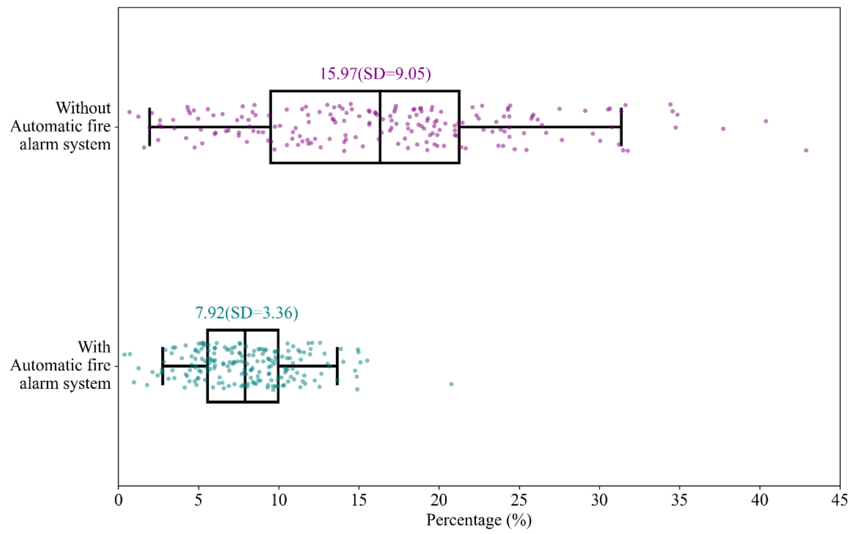

Figure14 The Percentage of Death in Social Force Evacuation

(2) When applying the social force evacuation strategy, the percentage of injuries (y_3) also decreases. According to the results in Figures 15 and 16, the injury percentage under the normal evacuation mode is 30.78% (SD=3.48%), and then slightly decreases to 25.74% (SD=4.41%) in Figure 16. Statistically, these values do not show a significant difference, indicating minimal changes in injuries. For the counterfactual scenario (with a functioning fire alarm system), the injury percentage is 18.55% (SD=5.33%), slightly reduced to 15.55% (SD=5.33%). Statistically, these values also do not show a significant difference. Therefore, two conclusions are drawn: employing a social force model during evacuation may slightly reduce injuries, and this model is robust whether or not a fire alarm system is installed. These results demonstrate the effectiveness of the social force model as a dominant evacuation strategy. Although injuries do not decrease significantly, the number of deaths can be greatly reduced.

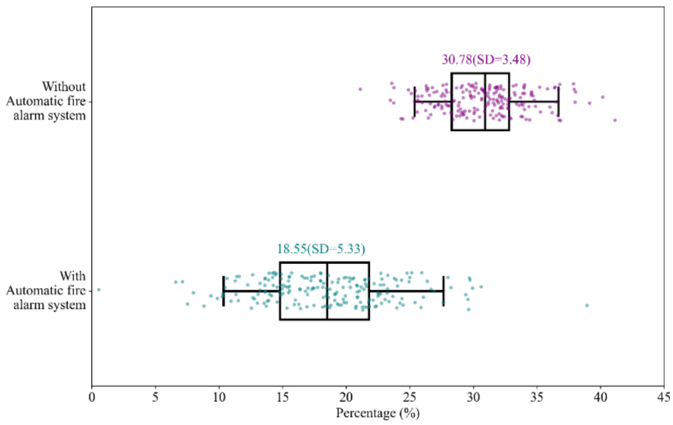

Figure15 The Percentage of Injuries in Normal Evacuation

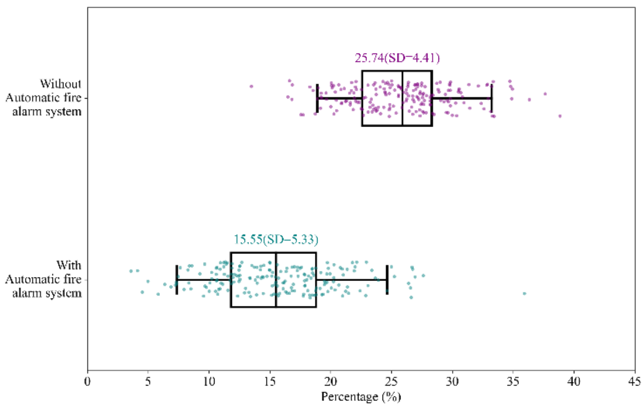

Figure16 The Percentage of Injuries in Social Force Evacuation

3.3 Single-damage immunity pattern

During fire evacuations, individuals are susceptible to injuries or even fatalities due to flames and dense smoke. This study introduces self-rescue skills as a simulation of how individuals can mitigate the effects of fire hazards by taking proactive measures. Self-rescue measures refer to actions and methods that individuals can utilize on the fireground, such as covering the nose and mouth, or moving in a crouched position, to reduce the damage caused by flames and smoke to the body. Previous research has demonstrated that survival skills significantly influence personal behaviors, survival techniques, and evacuation strategies during a fire. Behavioral skill training is practical for acquiring survival skills and enhancing personal safety. In the Anyang Kaixinda trade company fire, some employees applied survival skills during evacuation, such as evacuating via external stairs. In this study's simulation, it is assumed that some agents possess and can proficiently apply survival skills. Self-rescue skills are represented in the form of smoke and fire immunity to further explore the relationship between fire injuries, smoke injuries, and self-rescue skills. The study discusses the injuries suffered by the population during fire evacuation under two scenarios: the first only considers flame injuries, ignoring smoke injuries; the second only considers smoke injuries, ignoring flame injuries. The range for fire immunity in self-rescue skills is {0.1, 0.2, 0.3, 0.4}, and for smoke immunity is {0.05, 0.1, 0.15, 0.2}. This translation aims to match the expression standards of a top-tier academic English journal.

(1) Fire immunity does not significantly reduce the number of deaths(y_2). In this simulation, only flame damage was considered, excluding smoke damage. Using real case results as a baseline, the mortality rate was 36.21%. The simulation explored the impact of survival capabilities (the percentage of agents with survival skills) and different degrees of fire damage immunity. In Figure 17, it appears that both increasing fire damage immunity and enhancing survival skills lead to a reduction in mortality rates. For instance, with fire damage immunity fixed at 0.4, the mortality rate is 22.56% when 20% of individuals have skills to resist fire damage. Conversely, when 100% of individuals possess skills that mitigate fire damage, the mortality rate drops to 15.43%. This indicates that the use of appropriate survival strategies can decrease fatalities caused by fires. Consequently, more individuals survive the fire, although they all suffer injuries to varying degrees. This translation aims to meet the standard of top-tier academic English publications.

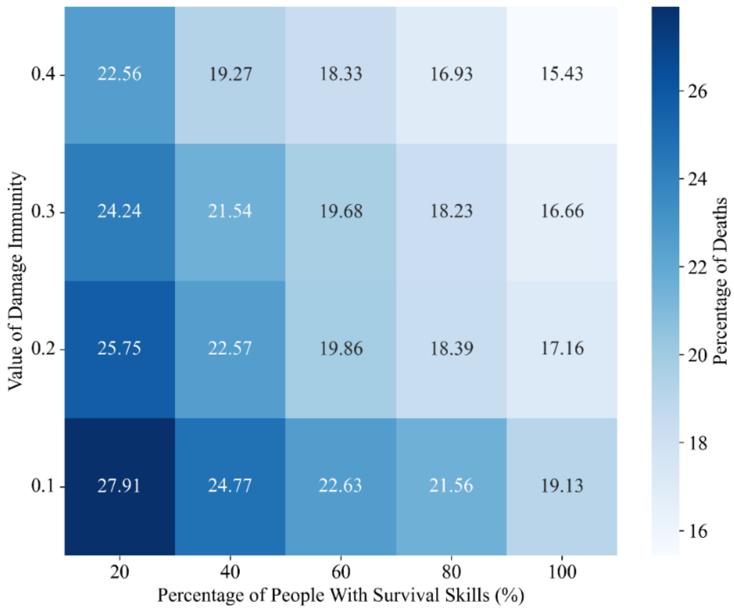

Figure17 Percentage of Deaths With Immune to Fire

(2) Smoke immunity significantly reduces the number of deaths(y_2). In this scenario, only smoke damage to the group is considered, while flame damage is ignored. Figure 18 demonstrates that as the survival rate increases, the mortality rate decreases. For instance, if we fix the immunity to smoke damage at 0.2, the mortality rate drops from 20.56% to 16.41%. This indicates a distinct trend between fire damage and smoke damage. Compared to the actual case scenario, the mortality rate is relatively lower for all individuals. With the use of survival skills to mitigate smoke damage during the fire, more individuals can survive. The percentage of deceased agents decreases as the percentage of proficient agents increases, because more individuals can use survival methods to protect themselves from the harm caused by smoke. This translation aims to meet the standard of top-tier academic English publications.

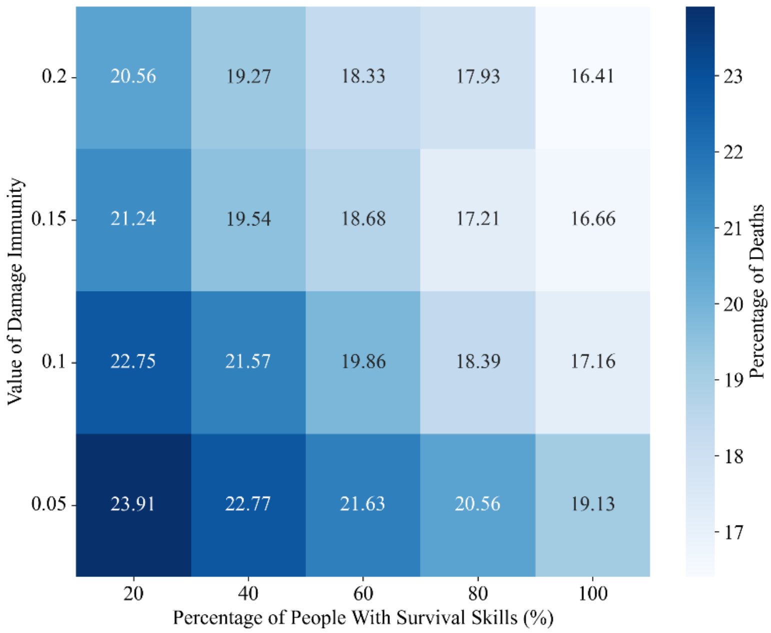

Figure18 Percentage of Deaths With Immune to Smoke

(3) Immunity to both types of damage increases survival time(y_1). According to Figures 19 and 20, as the percentage of individuals with self-rescue skills increases, the survival time (y_1) also gradually extends. Additionally, as the level of damage immunity rises, the survival time(y_1) becomes progressively longer. By comparing the two modes, we can conclude that survival skills enable residents to achieve a longer survival time than the actual scenario (T≈600 ticks), owing to their effective use of survival skills during the fire. Moreover, survival skills might provide residents under the fire immunity mode with longer survival times compared to those in the smoke immunity mode. This is because smoke damage is persistent and harder to prevent. Furthermore, residents can avoid direct contact with flames by covering themselves with wet materials, hence the more significant impact of fire damage immunity on outcomes. This translation aims to meet the standard of top-tier academic English publications.

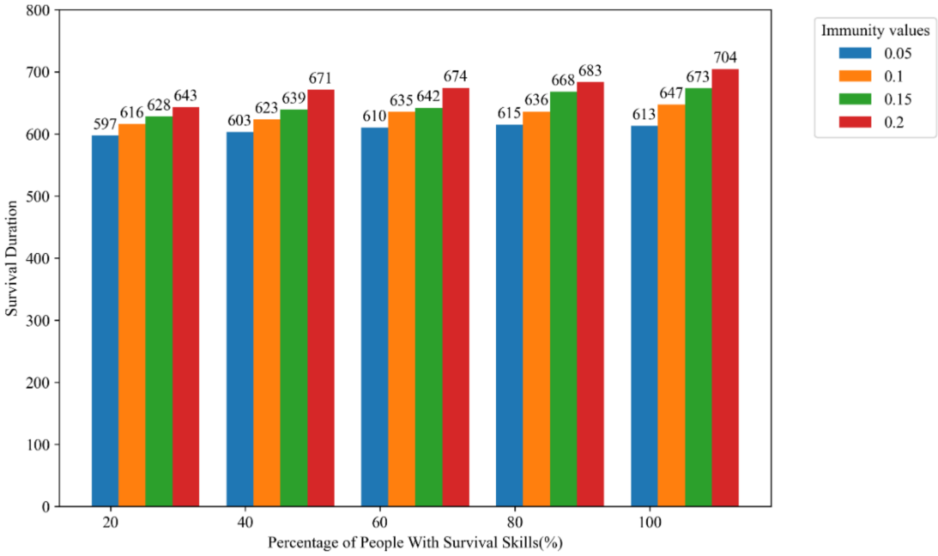

Figure19 Survival Duration With Immune to Fire

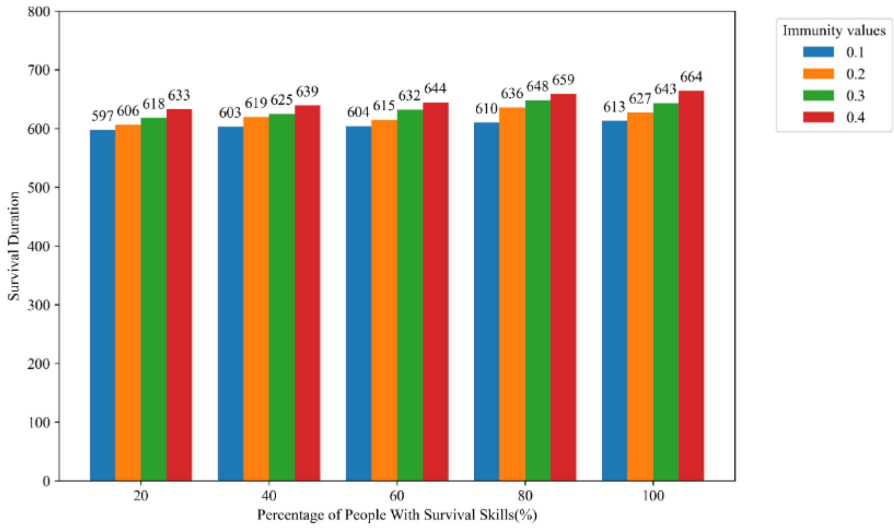

Figure20 Survival Duration With Immune to Smoke

3.4 Dual-damage immunity pattern

In the previous section, we discussed the impact of individual survival skills on survivability during a fire. However, in real fire evacuation scenarios, individuals are often simultaneously exposed to both flames and smoke, and they may possess multiple self-rescue skills. Based on these considerations, this section explores scenarios where individuals have both flame and smoke immunity. Simulation results demonstrate that having both types of immunities significantly enhances survival prospects during a fire. This translation is tailored to meet the standards of top-tier academic English publications.

Dual immunity significantly reduces the number of fatalities(y_2), but there is a slight increase in injuries(y_3). As shown in Figures 21 and 22, the simulated mortality rate is relatively low, while the injury rate is higher than the actual scenario. This occurs because, in our simulations, some fatalities are converted to injuries. Survival skills ensure that agents, who might otherwise have died, survive albeit with injuries. The more residents who possess survival skills, the fewer the fatalities and the more the injuries, which is ideal for societal safety. The higher the damage immunity, the fewer the fatalities and the more the injuries. With the same proportion of skilled individuals, the group with the highest damage immunity does not necessarily have the fewest fatalities or the most injuries. Fire scenarios are complex and dynamic, making them challenging to calculate and simulate. Maximizing damage immunity by mastering survival skills is crucial to achieving the goals of evacuation. This translation is tailored to meet the standards of top-tier academic English publications.

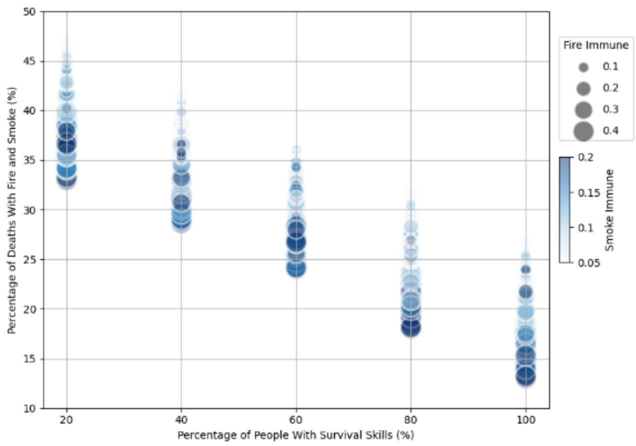

Figure 21 Percentage of Deaths with Fire and Smoke vs Survival Skills

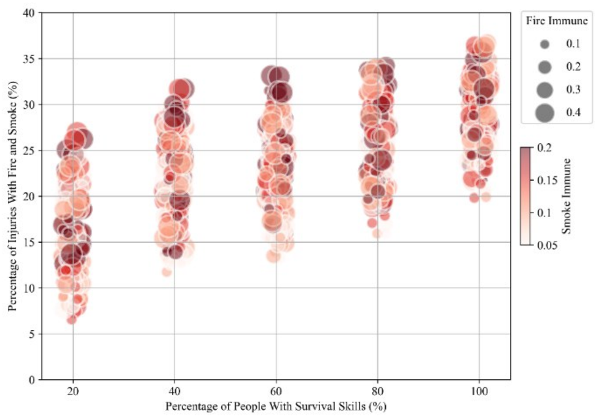

Figure 21 Percentage of Injuries with Fire and Smoke vs Survival Skills

IV. Conclusions

1. Conclusions and discussions

Due to its destructive nature and the sustained serious threats it poses to public life safety and societal stability, fire remains a significant challenge affecting public safety. This paper argues that individual self-rescue behaviors are crucial for successful evacuation from a fire scene, and agent-based modeling (ABM) can provide a reliable explanation for the evacuation process. This study selects the Anyang Kaixinda fire incident as a real case, which is a typical steel structure fire case, exploring the Anyang Kaixinda fire case reveals possible evolutions in similar structures. We focus on the self-rescue skills and behaviors of agents in building fires. Based on simulation data, we have obtained findings and discussions on fire alarm systems, individual behaviors in stairwells, and survival skills during a fire. Due to model simplification and idealization, our approach also exhibits a strong level of abstraction. Although our results are based on one case, the outcomes from the abstract model are generalizable and do not change with slight variations in specific parameters. Based on our study, the following strategies can guide individual behaviors and public responses to fires.

(1) Fire alarm systems can reduce deaths and injuries. Firstly, the presence of a fire alarm system significantly reduces the numbers of deaths and injuries, allowing residents to receive timely fire alerts and evacuate quickly. Secondly, as the size of the crowd increases, the impact of the central alarm system on deaths and injuries decreases, but it still performs better than real scenarios without the system. Therefore, installing central alarm systems in buildings is essential. Additionally, lessons from the Anyang Kaixinda fire suggest that the number of people in steel structure buildings should not be excessively increased, and interior density should be controlled.

(2) Expanding social force evacuation can prevent jostling, thus reducing casualties. We introduced crowd pushing into the model to adapt to real situations. We also proposed a practical social force evacuation strategy to avoid jostling during panic descents. The results confirmed the effectiveness of our social force evacuation. Governments should apply the principles of expanded social force models to organize fire evacuation drills. Residents proficient in these evacuation skills can reduce unnecessary risks.

(3) Survival skills reduce deaths. We can minimize societal losses as much as possible through survival skills. However, the impact of survival skills on smoke damage is limited, and permanent damage caused by smoke cannot be well prevented. We should pay more attention to smoke during fires. In the dual-immunity mode, the number of

deaths under each parameter combination is lower than in real situations. Moreover, survival skills help reduce injuries and deaths in simulations. Regarding survival time, survival skills help individuals survive longer. For each damage immunity mode, the simulated survival time is higher than in real situations, increasing the likelihood of successful escape. Therefore, governments and communities should prepare more smoke masks in high-rise buildings. At the same time, every company should make emergency preparations, such as purchasing protective materials, learning self-rescue knowledge, and participating in fire drill training.

(4) Limitations and future work. We have constructed a highly idealized model of crowd dynamics and human behavior during fire evacuations. Actual evacuations are more complex and involve more responses, such as panic, collective irrationality, imitation, emergence of leaders, and external rescue factors. These mechanisms have varying impacts on fire evacuations. In further studies, many assumptions and simplifications need to be improved to examine interactions among individuals. Other significant factors should be introduced into the model, such as emotions, external firefighters, and concurrent disasters.

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