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Article

The role of altruistic behavior in emergency evacuation: A simulation study

Jianxun Li[1], Chao Wang[1], Jim Q. Chen[2,*], Hassan Talal Khan[1]

[1] School of Economics and Management, Xi'an University of Technology, Xi'an 710048, China
[2] Herberger Business School, St. Cloud State University, Saint Cloud, MN 56301, USA
*** Corresponding author:** Jim Q. Chen, jchen@stcloudstate.edu

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Abstract: Given the rising threat of terror attacks and the increasing frequency of natural disasters attributed to climate change, enhancing evacuation capacities in various spaces has become crucial for saving lives and accelerating recovery processes. This study investigates the influence of altruistic behavior on evacuation efficiency by developing a social force model that categorizes individuals into three demographic groups: youth, middle-aged, and seniors. Simulation experiments based on the model were conducted to evaluate the impact of altruistic behavior on evacuation efficiency under different conditions, such as evacuation capacity, reliability, and recovery time. The simulation results show that a higher probability of falling leads to longer evacuation times. While an increase in the probability of altruistic behavior improves evacuation efficiency, excessive altruistic behavior causes evacuation times to vary in a zigzag pattern. When the help range exceeds 0.7m, evacuation efficiency fluctuates without a clear trend of improvement.

Keywords: emergency evacuation; social force model; altruistic behavior

1. Introduction

In the event of an emergency, maximizing the saving of lives and property and achieving rapid evacuation have become important research topics. To effectively evacuate people in a specific space, many research studies have been carried out. Among them, micro-model-based simulations have been highly valued by experts and scholars. This stream of research can be divided into two categories: the social force model and the cellular automata model. The social force model (Bosina and Weidmann, 2017) combines psychological vectors of evacuees' expectation for fast escape, the psychological-social desire for interpersonal space, and obstacle avoidance actions. Under different building layouts and individual characteristics, the social force model simulates the evacuation direction and efficiency in a continuous, real-time process to achieve the optimal evacuation results. The cellular automaton model (Burstedde et al., 2001) divides the terrain into cell spaces of the same size and constructs static and dynamic fields according to the evacuation terrain. The cellular automaton model simulates the continuous iterative movement of evacuees. At each iteration, each evacuee decides which direction to move and then takes his or her adjacent cell if it is not occupied.

Helbing et al. (2000) used the social force model to simulate individual and herding behavior under escape panic situations. The simulation results are consistent with the empirical observations in real life, thereby proving the model's robustness. Utilizing the cellular automata model, Kirchner et al. (2002) conducted a study on the repulsive interaction force among evacuees, the static floor field that determines the direction of movement, and the dynamic floor field that guides individuals away from high-density areas. Their findings revealed that to achieve optimal evacuation times, a careful balance between herding behavior and awareness of the surrounding environment is necessary. In other words, it involves restraining from entering overly crowded areas and using knowledge about the shortest routes to the exits. Zhou et al. (2009) introduced a pairing behavior into the cellular automaton model. They discussed the mutual effect between different types of evacuees and confirmed that the pairing behavior contributed to the optimization of evacuation time. Li et al. (2020) analyzed the psychological changes of evacuees in the evacuation process and demonstrated through simulation experiments that the panic psychology of evacuees would hinder the effective implementation of the evacuation plan. In addition, Burstedde et al. (2001) and Song et al. (2020) verified that when the crowd avoidance probability is suitable for evacuation scenarios and personnel distribution, the evacuation process can be shortened. By analyzing the issue of evacuation in elderly care facilities, Zhuo et al. (2022) and Huo et al. (2022) proposed that the elderly or the vulnerable individuals should form evacuation groups with younger evacuees to improve evacuation capability. They proved that the increase in the proportion of vulnerable individuals will increase the evacuation time, and the location distribution of vulnerable individuals will affect the evacuation efficiency.

Through the literature review, it can be found that the existing research mainly focuses on the mutual effect of different types of evacuees, such as panic propagation (Kirchner and Schadschneider, 2002), cooperation under competition (Li et al., 2020), crowding phenomenon (Li and Zhang, 2021), behavioral characteristics (Liu, 2020), disaster avoidance psychology (Song et al., 2020) and individual behavior (Yang, 2020). At the same time, the loss of mobility of evacuees caused by panic psychology, crowding, etc. are also widely discussed. However, there is little discussion on the role of altruistic behavior. Only Gao (Yu, 2018) built a cellular automaton model based on altruistic behavior and preliminarily analyzed the group evacuation behavior between the helper and the assisted. The altruistic behavior has not been introduced into the social force model, and the temporary loss of pedestrian evacuation ability caused by sudden falls has not been considered. More importantly, there is a lack of in-depth impact analysis of the altruistic behavior on the evacuation process. Therefore, this research employed simulation studies based on the social force model to investigate the impact of the altruistic behavior on the evacuation efficiency under different personnel proportions and help probabilities. The simulation results revealed a critical point of help range and help probability that may have a significant impact on the evacuation efficiency.

2. A modified social force simulation model with altruistic behavior

The social force model (Bosina and Weidmann, 2017) is based on Newtonian dynamics. It describes the motion of pedestrians driving by various forces reflecting internal motivations and external impacts. It can effectively simulate pedestrians' motion and speed as observed in the real-world settings. By adding altruistic behavior, the model describes the individual's altruistic role through four stages: perception, decision-making, helping, and disengagement.

2.1. Basic social force model

During an evacuation, the movement direction of an individual is determined by his or her desired destination, the tendency to keep social distance with other people, and the direction to avoid obstacles. In the social force model proposed by Helbing (Bosina and Weidmann, 2017), the real-time motion vector of personnel is composed of the expected motion vector, the repulsive interaction force among people and obstacle avoidance vector. In mathematical terms, the change of velocity in time t can be calculated by the following equation:

$$m_i \frac{d\vec{v}_i(t)}{dt} = \vec{F}_i^{drv}(t) + \sum_{j \neq i} \vec{F}_{ij} + \sum_{w} \vec{F}_{iw}(t) \tag{1}$$

In Equation (1), m_i and $v_i(t)$ are respectively the mass and speed of pedestrian i at time t. Pedestrian i is subjected to a total of three forces, namely, the self-driving force vector $\vec{F}_i^{drv}(t)$ of pedestrians, the force vector $\vec{F}_{ij}(t)$ of other pedestrians j on i, and the force vector $\vec{F}_{iw}(t)$ of walls or obstacles w on i. Where in the self-driving force vector $\vec{F}_i^{drv}(t)$ of pedestrians is expressed as:

$$\vec{F}_i^{drv}(t) = m_i \frac{v_i^0(t)\vec{e}_i^0(t) - \vec{v}_i(t)}{T_i} \tag{2}$$

It means that pedestrian i expects to accelerate from the current speed vector $\vec{v_i}(t)$ to the maximum movement speed vector $v_i^0(t)\vec{e}_i^0(t)$ within time T_i, where $v_i^0(t)$ is the maximum movement speed for pedestrian.

For the force vector $\vec{F}_{ij}(t)$ of other pedestrians j to i, each pedestrian is expected to maintain a certain distance from other pedestrians and will generate elastic force when people contact. This effect can be characterized by repulsion force $\vec{F}_{ij}$.

$r_{ij} = r_i + r_j$, and r_{ij} is the sum of the radius r_i of pedestrian i and the radius r_j of pedestrian j. d_{ij} is the distance between the center of pedestrian i and the center of pedestrian j, and $\vec{n}_{ij}$ is the unit vector from i to j. A_i and B_i are constants, specific to pedestrian i. The constant A_i is a scaling factor that determines the strength of the repulsive force for pedestrian i. The constant B_i is a decay factor that determines how quickly the repulsive force deminishes as the distance between pesdestrain i and j increases. k is the size standard of elastic force when contacting, and κ is the size standard of sliding friction force when contacting, then $\vec{F}_{ij}(t)$ can be expressed:

$$\vec{F}_{ij}(t) = \left\{A_i\, exp\left[\frac{r_{ij} - d_{ij}}{B_i}\right] + kg(r_{ij} - d_{ij})\right\}\vec{n}_{ij} + \kappa g(r_{ij} - d_{iw})\Delta v_{ji}^t \vec{t}_{ij} \tag{3}$$

Similar to the force between pedestrians, if d_{iw} is the distance from the center of pedestrian i to obstacle w, the force exerted by obstacle w on pedestrian i is expressed as follows:

$$\vec{F}_{iw}(t) = \left\{A_i\, exp\left[\frac{r_i - d_{iw}}{B_i}\right] + kg(r_i - d_{iw})\right\}\vec{n}_{iw} - \kappa g(r_i - d_{iw})(\vec{v}_i \times \vec{t}_{iw})\vec{t}_{iw} \tag{4}$$

2.2. Altruistic behavior description

People may fall during an emergency evacuation due to a variety of factors, including tripping, stumbling, being pushed. However, evacueers' age and fitness condition can be important factor to consider. For the convenience of description, this paper divides the evacuees into three categories: young, middle aged, aged people.

Young people move the fastest, followed by middle aged people, and aged people. Each category of evacueers is assigned with a certain level of probability of falling. An evacuee's status during an evacuation may be described by one of the following three types: normal, falling, and helping. After falling, the personnel status changes from normal to falling. It is assumed that certain probability exists for a person to assist a fallen person if it is within the person's help range. Once a person starts to assist a fallen person, his or her status changes from normal to helping. When the fallen person regains his or her balance, the status is changed back to normal, so does the helper's. Altruistic behavior in an emergency evacuation can shorten the time for fallen people to recover their ability but it may also slow down the evacuation process as a whole.

The altruistic behavior in the evacuation process is divided into four steps: perception, decision-making, helping and disengagement, as shown in **Figures 1** and **2**. (1) Perception: Before model iteration, each evacuee in normal state perceives if there are evacuees in fallen state within their help range; if yes, they will enter the decision-making stage. (2) Decision making: he or she decides whether to help the fallen person. (3) Helping: if the decision is yes, the helper enters into helping state. The recovery process starts until the fallen person regains postural recovery. (4) Disengagement: The decision to disengage is made according to the remaining recovery time of the fallen person. When the remaining recovery time is exhausted, the fallen person returns to the normal state and then the two are disengaged and proceeded to their remaining evacuation process.

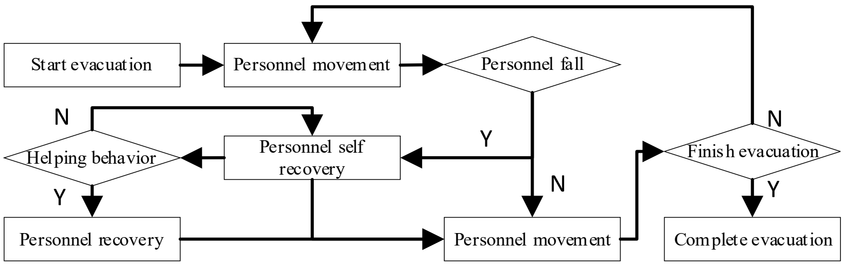

Figure 1. Evacuation flow chart.

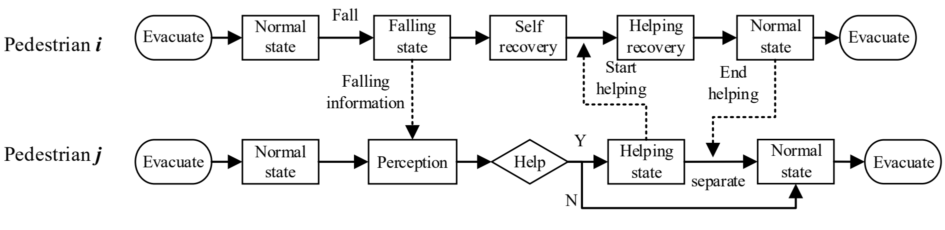

Figure 2. Change of personnel status in helping process.

In the process of perception, a person will first observe whether there are fallen people within the range of help. Assume that the fallen person is i, the normal person is j, and the distance between the person i and the person j is dis_{ij}. Define Dis as a help range. If $0 \leq dis_{ij} \leq Dis$, the fallen person i is within the help range of person j; if $dis_{ij} > Dis$, the fallen person i is not within the help range of person j.

In the decision-making process, the model will generate a random number hp for the normal person, which is used to decide whether the normal person help the fallen person within the range of help. The model will initialize a help probability P_h according to the person's type. The random number hp is a value in the range of $[0,1]$. If $0 \leq hp \leq P_h$, the person will help the fallen person, otherwise, the person will not provide any help.

In the process of helping, the remaining recovery time of the fallen person will decrease rapidly. The time interval of model iteration is θ seconds. Each time step of the fallen person in the process of self-recovery will reduce the remaining recovery time by θ second. However, each time step of the fallen person with a helping person will reduce the remaining recovery time by θ/F second. F is the reduction factor of help, and it is confined to the range of $(0, 1)$. Parameter F is determined according to previous relevant studies.

In the process of disengagement, the remaining recovery time of a fallen person is calculated at each time step. If the remaining recovery time decreases to zero, the altruistic behavior ends. Then the status of the fallen person is changed to normal state. Both return to their own evacuation process.

In addition, when more than one person observed a fallen person within the help range, the fallen person and all evacuees within the help range will enter the help decision process accordingly. Each fallen person can only be assisted by one helping person. In this paper, we consider three kinds of help processes: (1) The fallen person is helped throughout the recovery process. Therefore, the actual self-recovery time is $T = 0$ s, $T^* = F \times TD$; (2) The fallen person is helped halfway, and self-recovery time is T seconds, $T^* = T + F \times (TD - T)$; (3) The fallen person receives no help, and actual recovery time is $T^* = TD$. $T^*$is the actual recovery time of the fallen person, TD is the time required for the person to recover himself/herself without any help; and T is the time of self-recovery before a helper arrived.

3. Methodology of modeling and evacuation simulation

To simulate how the help probability and help range affect evacuation under different fall probabilities and falling time, we adopted multi-agent technology to model the human evacuation process. Considering the differences of individual behavior and cognition in evacuation, evacuees are divided into three categories: the elderly, the middle-aged, and the young. The multi-agent technology in artificial intelligence theory is used to build the evacuation model. In the system, the evacuation process is seen as a system in which multiple agents work cooperatively. Personnel are regarded as agents with their action capabilities, able to independently make decisions and execute actions. Each agent independently chooses its moving direction and speed. At the same time, each agent can influence other agents around them with the ability to help. The properties of the agent are described by the spatial position, moving speed, etc. These properties are changed by the influence of other agents. Additionally, the surrounding environment is abstracted into a simple rectangular area to reduce the influence of non-major factors on the evacuation results. This evacuation environment corresponds to an idealized evacuation scenario, providing a clear safe position during the evacuation process, and serving as the outermost constraint condition to limit the agents' activity range and action goal.

In the evacuation simulation, we first set up the exit location and the evacuation environment in the multi-agent system. At the same time, the space location and size of evacuation scenario represented by evacuation environment are given, and the initial number of agents is set according to the collected field data. Moreover, the values of the agent's help probability, help range, fall probability, falling time, etc., are assigned. Secondly, we set the step time of the simulation clock and used visual aids (icons) to represent the three different groups of people. These different shaped icons are required not to overlap in the space. Then, the simulation is carried out according to the step size. During the simulation, all agents operate within each step period. Each agent carries out its move, helping, and falling according to its given probabilities. The system checks whether the behavior of each agent exceeds the evacuation environment. If it does, it will be corrected; if not, the behavior changes its own state and the state of surrounding agents. This process continues, with the system iterating through each agent's behavior and state changes, until all agents have successfully reached the designated safe area.

4. Simulation of evacuation considering altruistic behavior

To verify the impact of the altruistic behavior on the evacuation process, a 65 m long and 40 m wide space area is constructed using the anylogic simulation software with multi-agent to represent the internal space of a building. There are two exits, which are respectively set in the middle of the 40 m building wall, see **Figure 3**.

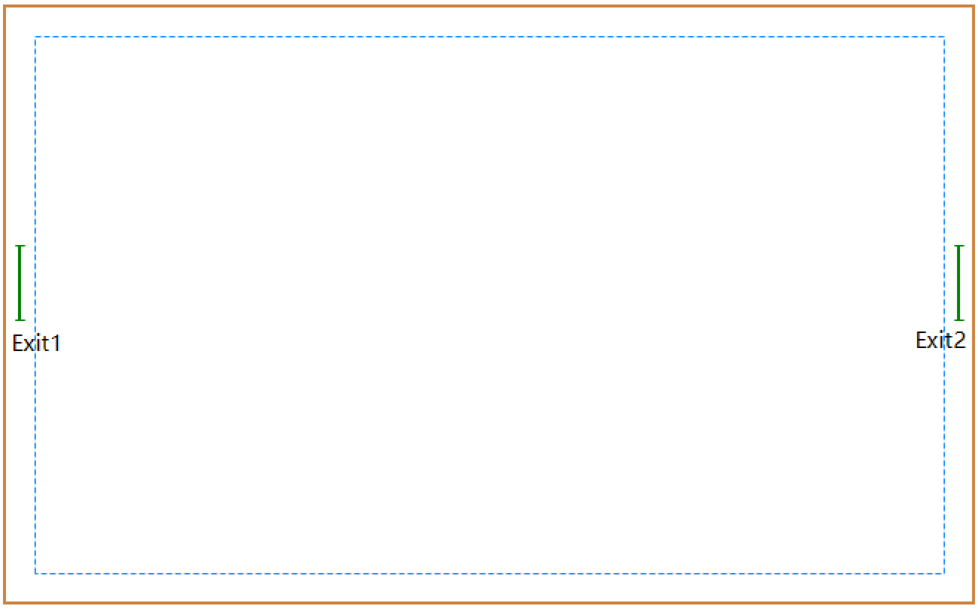

Figure 3. Evacuation building chart.

The basic parameters of the three age groups used in the simulated crowd (young, middle aged, and seniors) are shown in **Table 1**. The rectangular symbols in the simulation panel are agents representing the young people, the circular agent symbols represent the middle-aged people, and the triangular agent symbols represent the aged people. When the agent enters a fallen state, the agent symbol changes from hollow to shadow; When the agent's state changes to the helping state, the agent symbol changes from hollow to solid. On this basis, the preset simulation experiment data is shown in **Table 1**.

Table 1. Parameter description of three types of personnel.

Total number of people (Num)	**400**		
Personnel parameters	**Young personnel**	**Middle-aged personnel**	**Aged personnel**
Maximum movement speed (V_{mi})	2.0	1.5	1.0
Falling time (TD_i)	5	7	10
Personnel proportion (P_i)	0.3	0.4	0.3
Fall probability (P_{di})	0.01	0.015	0.02
Help range (Dis)	0.5	0.5	0.5
Probability of Altruistic Behavior y (P_h)	0.5	0.5	0.5
Reduction factor (F_i)	0.3	0.3	0.3
Normal symbol	Hollow rectangle	Hollow circle	Hollow triangle
Falling symbol	Hatched rectangle	Hatched circle	Hatched triangle
Helping symbol	Solid rectangle	Solid circle	Solid triangle

The maximum movement speed, which indicates the highest speed at which people can move during an emergency, is set based on references (Yu et al., 2022; Zhang et al., 2020). Generally, the reaction time of a normal person ranges between 0.2 and 0.3 s, while the speed in an emergency state is 6.25 m/s. For ease of calculation, we set the maximum movement speed of aged personnel to 1 unit, equivalent to 3.13 m/s. For middle-aged and young personnel, the maximum movement speeds are set to 1.5 units and 2.0 units, corresponding to speeds of 4.69 m/s and 6.25 m/s, respectively. The fall probability during the evacuation process is based on the casualty rates of historical stampedes (Zhang, 2017; Zhang et al., 2015).

The probability of altruistic behavior represents a person's likelihood of helping others during an emergency. We assume a 50% chance of altruistic behavior, reflecting a general tendency towards helping others. Correspondingly, the reduction factor, which indicates the decrease in recovery time, is initially set at 0.3 units. The help range represents the maximum distance within which assistance can occur between the helper and the person being helped. This is defined as a circular area with a radius of 0.5 m, considering that people can help others within the reach of their outstretched arms, regardless of age.

The Falling time refers to the duration a person remains on the ground after falling, based on references (Helbing et al., 2000; Zhang et al., 2022). It is important to note that falls during emergencies often lead to stampedes, causing individuals to remain on the ground for extended periods, making it difficult to get up quickly. Therefore, the falling times for the three types of personnel are set at 5 s, 7 s, and 10 s. Using these preset simulation parameters, multiple simulation runs were conducted to assess the impact of changes in parameters such as fall probability, help probability, and help range.

4.1. Impact of fall probability on evacuation process

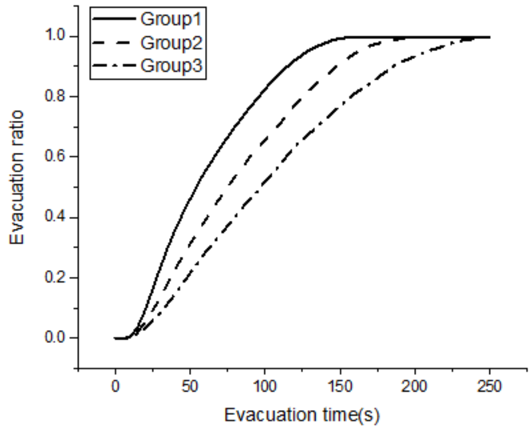

Figure 4. Effects of three fall probabilities on evacuation time.

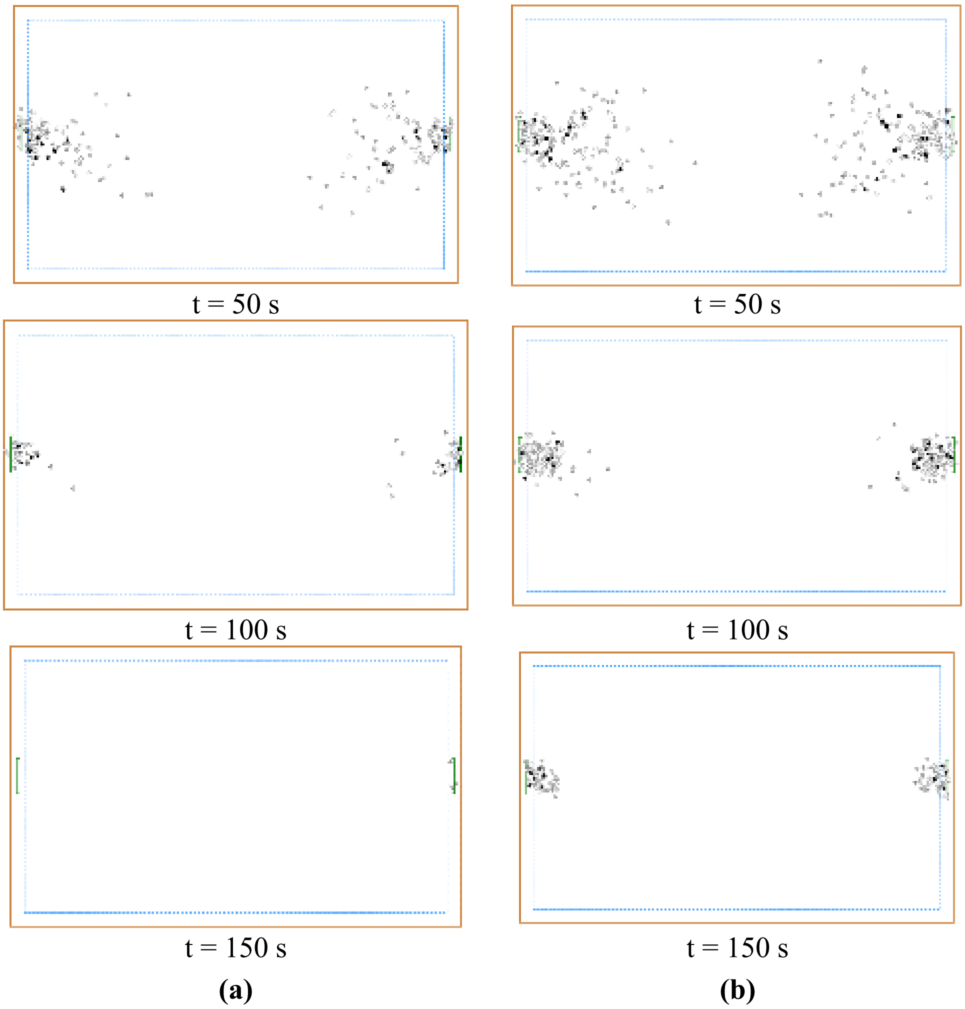

Figure 5. Comparison of the low fall probability and the high fall probability groups: **(a)** Low fall probability group; **(b)** High fall probability group.

The occurrence of falls is bound to have a negative impact on the evacuation process, but it is still worth discussing the extent of the impact under the condition of altruistic behavior. Therefore, under the condition that all simulation parameters remain unchanged, three groups of different fall probabilities are set to explore the impact through comparative experiments: (1) Group1 (low falling probability): $P_{d1} = 0.005$, $P_{d2} = 0.01$, $P_{d3} = 0.015$; (2) Group2 (medium falling probability): $P_{d1} = 0.01$, $P_{d2} = 0.015$, $P_{d3} = 0.02$; (3) Group3 (high falling probability): $P_{d1} = 0.015$, $P_{d2} = 0.02$, $P_{d3} = 0.025$.

The simulated evacuation results are shown in **Figures 4** and **5**. It is apparent that the increase of fall probability will cause significant delay in the evacuation time. As shown in **Figure 4**, in the low fall probability group, 99% of the people were evacuated in 150 s, but in the medium fall probability group, achieving the same percentage took 190 s. In the high fall probability group, it took 250 s. In addition, the evacuation effectiveness differs most among the three groups during the time period of 25 s to 250 s. **Figure 5** shows snapshots of the distribution of people in the evacuation process at different point of time. The increase of fall probability leads to an increase in the number of fallings, slower individual evacuation, a sharp decline in the effectiveness of evacuation. Although the fall probability of the three groups is set at a 0.5% increment, the evacuation time was increased by 26% and 66% respectively in-between the groups. Compared with the low fall probability group, the evacuation speed of the high fall probability group showed a lag, and the crowd gathered at the exit for a longer time.

4.2. Impact of the probability of altruistic behavior on evacuation process

When a person falls, he will try to regain his balance by himself, or may receive help from nearby person. To explore the impact of different probabilities of altruistic behavior on the evacuation process, the help range is fixed at 1.5 m ($Dis = 1.5\ m$) and other parameters remain unchanged. The help probabilities used in the simulation experiments are $P_h = \{0.1, 0.2, 0.3, \cdots, 1.0\}$.

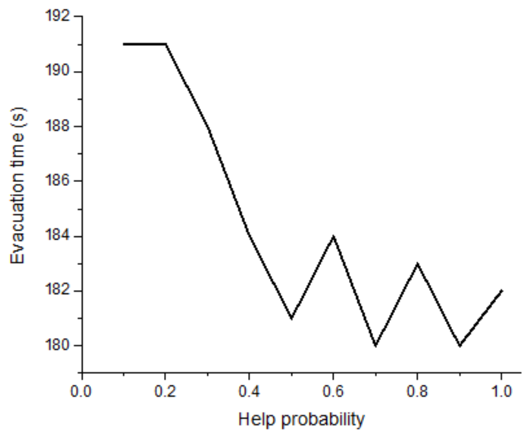

Figure 6. Effects of different probability of altruistic behavior on evacuation time.

The simulation results are shown in **Figure 6**. When the probability is within the range (0.1, 0.4), the higher the probability, the higher the rate of people's ability to recover from falls, which positively promotes the reduction of evacuation time; when the probability is within the range (0.4, 1.0), the probability increase resulted in the small fluctuations in the evacuation time. **Figure 7** shows the positions of evacuees at selected points of time during the evacuation process. With the probability $P_h = 0.1$, the evacuation efficiency is reduced in the early stage of evacuation; In the middle of the evacuation, some people failed to reach the exit in time; In the later period of evacuation, some people fell after reaching the exit and aggravated the congestion. With the help probability $P_h = 0.9$, most people who fell got help in the early evacuation period; In the middle of the evacuation, most people reached the exit in time; In the later period of evacuation, timely help reduced the aggravation of congestion.

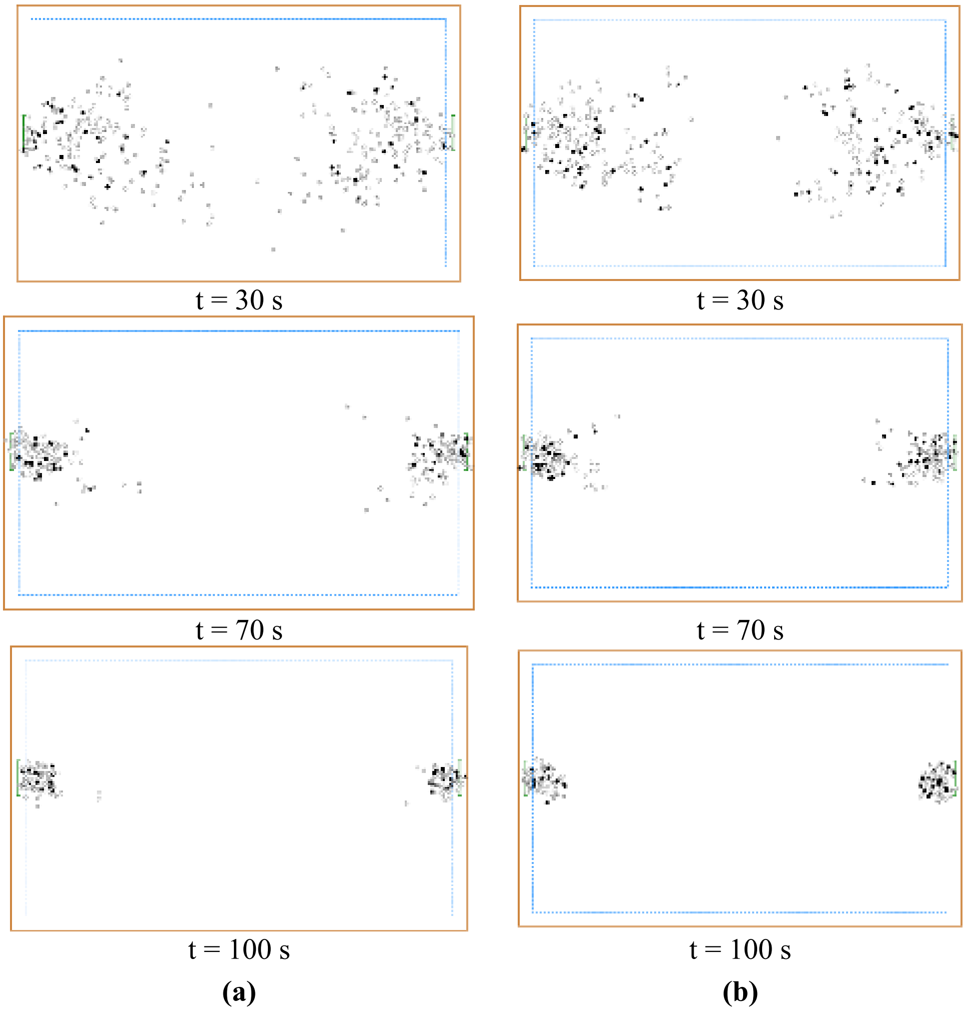

Figure 7. Comparison of $P_h = 0.1$ evacuation and $P_h = 0.9$ evacuation: **(a).** $P_h = 0.1$; **(b)** $P_h = 0.9$.

4.3. Impact of help range on evacuation process

During the evacuation process, when normal people encounter fallen people within the range of helping, they may help the fallen to recover quickly. To explore the impact of different help ranges on the evacuation process, the help ranges are set to be in $Dis = [0.5, 1.5]$ while all other parameters remain unchanged. **Figure 8** shows that the increase of the help range within $(0.5, 0.7)$ reduced the evacuation time dramatically. When the help range increased from 0.5 m to 0.7 m, the corresponding evacuation time is decreased by 8%; However, when the help range increased from 0.7 to 1.5 m, the evacuation time fluctuated slightly and showed no clear trend.

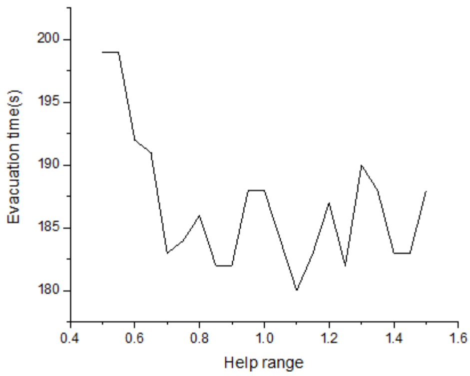

Figure 8. Evacuation time under different help ranges.

The simulation results are shown in **Figure 9**. When the help range is $Dis = 0.5\ m$, the evacuation efficiency of individuals who fell in the early stage of evacuation is low and can not be improved through altruistic behavior. This is because the scattered positions of people at the early stage make it difficult for normal and fallen individuals to establish a helping relationship.

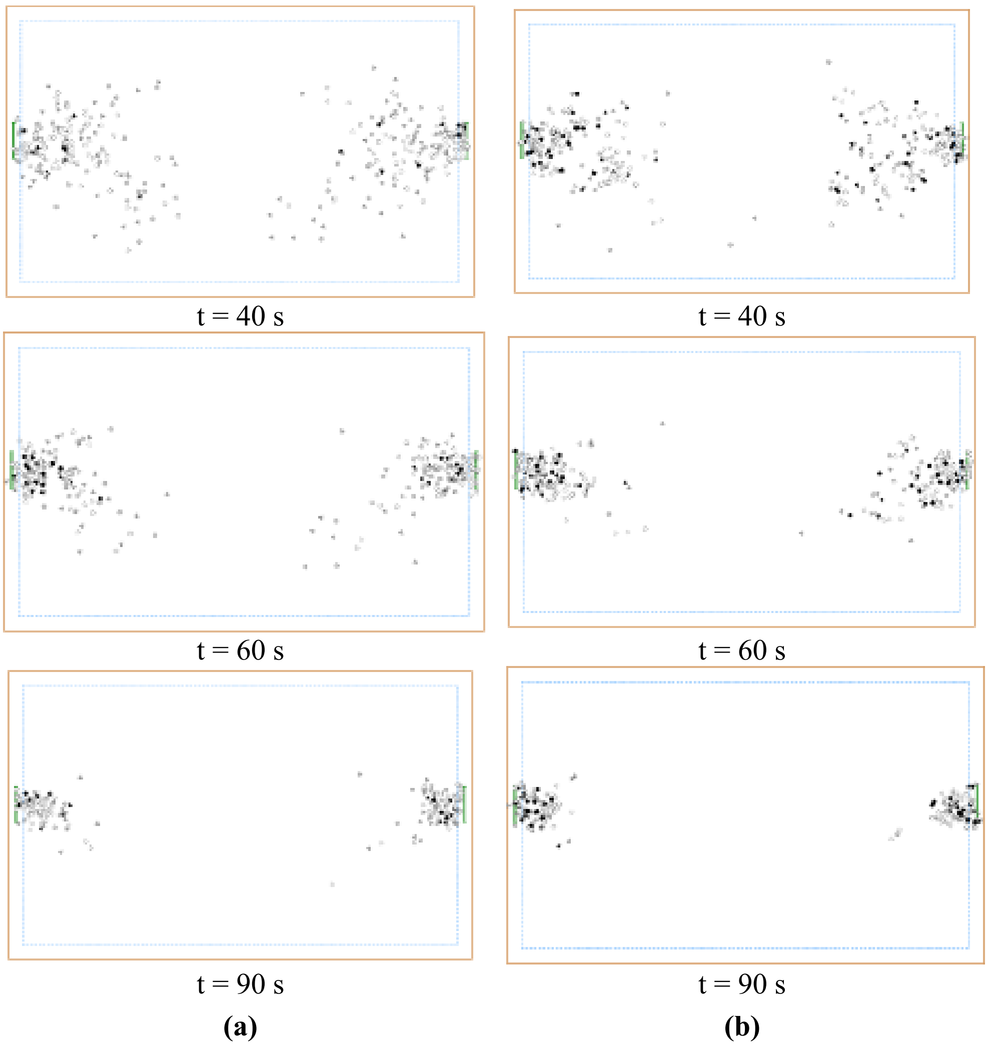

Figure 9. Comparison of $Dis = 0.5m$ evacuation and $Dis = 1.5m$ evacuation: **(a)** $Dis = 0.5\ m$; **(b)** Dis = 1.5 m.

In the middle stage of the evacuation, some individuals are far from the exits, and sporadic personnel fail to reach the evacuation exits in time. Conversely, when the help range is $Dis = 1.5\ m$, the evacuation efficiency is higher in the early stage, and congestion caused by falls is reduced through altruistic behavior. In the middle stage, most people successfully evacuated to the vicinity of the exits.

In the later stage of the evacuation, while most individuals reach the exits, the increase in density at the exits leads to a reduction in evacuation efficiency, consistent with the "fast is slow" principle observed in previous studies. This principle indicates that high evacuation efficiency creates bottlenecks at the exits, causing congestion and a subsequent decrease in evacuation speed.

4.4. Impact of personnel proportion on evacuation process

Different types of people have different evacuation speeds and falling times. Therefore, the proportion of people with different age is also an important factor in the evacuation process. The criteria this paper used to classify the three groups of personnel are based on the demographic data from China's census in 2010 and 2020. The young personnel include people aged 15–24, the middle-aged personnel include those in the age range of 25–54, and the vulnerable personnel are people under 14 and over 55 (Zhou et al., 2009; Zhuo et al., 2022). Under the condition that all simulation parameters remain unchanged, the proportion of three groups of personnel is set as (1) Group 2010: $P_1 = 0.17$, $P_2 = 0.47$, $P_3 = 0.36$; (2) Group 2020: $P_1 = 0.12$, $P_2 = 0.46$, $P_3 = 0.42$; (3) Control: $P_1 = 0.1$, $P_2 = 0.3$, $P_3 = 0.6$. Group 2010 consists of 17% young individuals, 47% middle aged, and 17% seniors. The percentages are from 2010 census. Group 2020 comprises 12% young individuals, 46% middle aged, and 42% seniors. The percentages are from China's 2020 census. The percentages used in the control group are based on the current demographic data of Japan.

The evacuation situation is shown in **Figure 10**. There was a significant difference in evacuation time among the three experimental groups. The evacuation time of the Group 2010 was the shortest, completing the evacuation in just 180 s. The evacuation time of the Group 2020 was in the middle, taking 220 s to complete the evacuation. The Control group took 260 s to complete the evacuation, which was the longest among the three experimental groups.

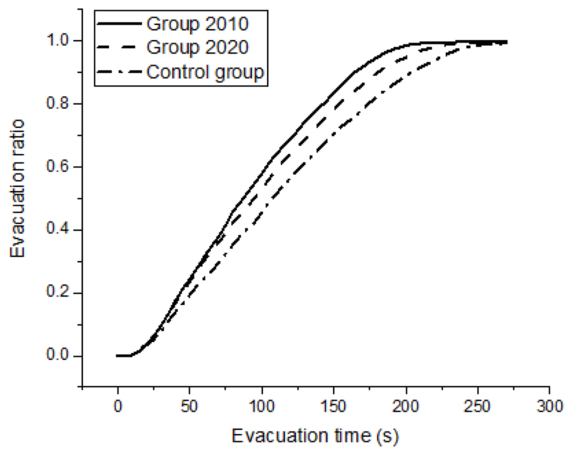

Figure 10. Evacuation time for different personnel proportion.

The simulation results are shown in **Figure 11**. Note that the control group in the **Figure 11** consists of more middle aged and seniors than that in the Group 2010. When t = 100 s, the overall evacuation process of the control group was slow, and the people in the control group were farther away from the exit than those in Group 2010. When t = 150 s, more people in the control group fell, who together with their helpers became temporary "obstacles", therefore, creating an "arching phenomenon" at the exits. On the other hand, the group 2010 had a much less severe problem due to its larger percentage of young people in the group.

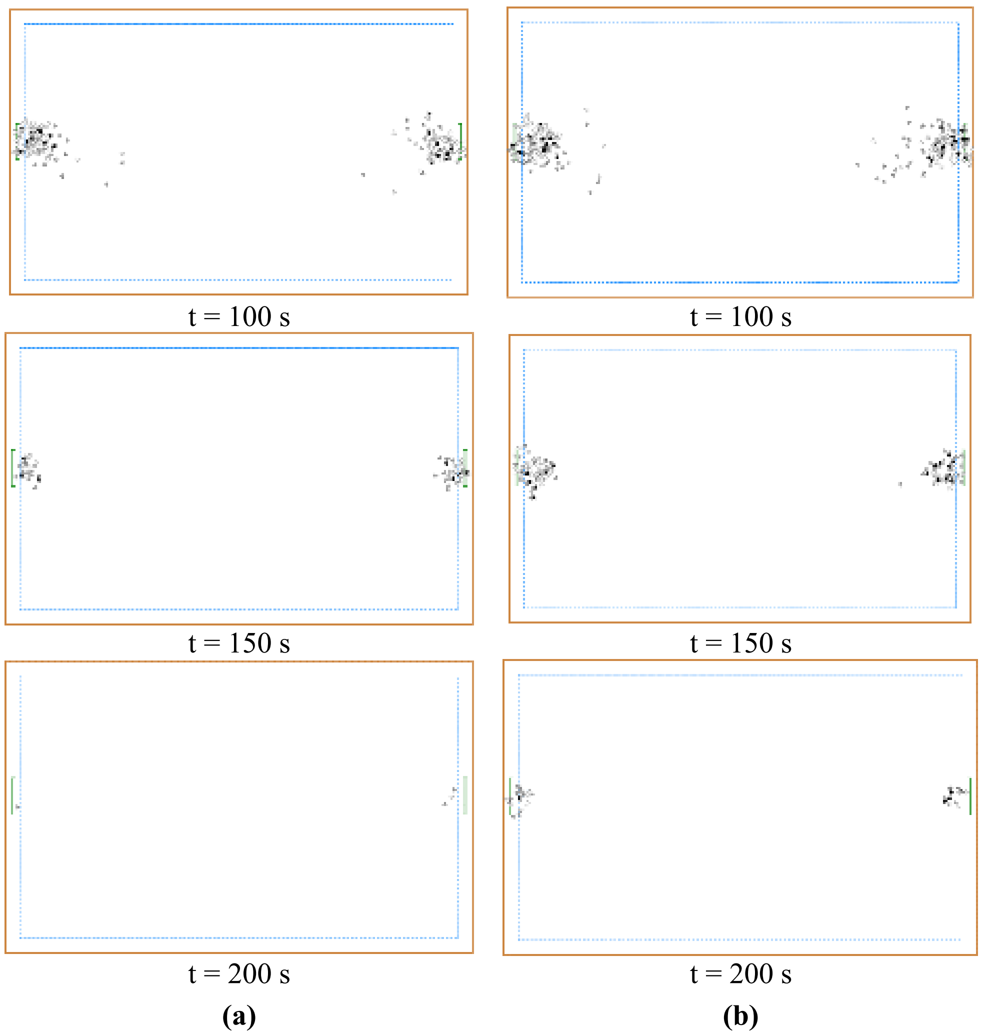

Figure 11. Comparison of Group 2010 evacuation and Control group evacuation: **(a)** Group 2010; **(b)** Control group.

When t = 200 s, the impact of falling people as "obstacles" in the control group is further magnified. At this time, the evacuation ratio of group 2010 has reached 99%, while that of the control group is only 88%. It is apparent that the composition of people with different age is also a factor that cannot be ignored in the study of evacuation process. In recent years, the aging trend in many societies has gradually intensified, which will lead to the reduction of evacuation capacity. If the evacuation effect is maintained, the help capacity needs to be further increased.

5. Discussions

When an emergency occurs, the evacuation process is often affected by many factors and is inherently complex. Therefore, in the study of emergency evacuation, it is necessary to abstract the entire system, extract the primary factors for analysis, and simplify the constraints. It is generally understood that altruistic behavior often positively affects group activities, but such behavior can also cause chaos. Hence, this paper focuses on analyzing the extent to which altruistic behavior is conducive to efficient personnel evacuation.

(1) The influence of falling behavior on evacuation is significant. The experiments with three groups of personnel, each with different fall probabilities, showed that the group with high fall probability had a consistently low ratio of successful evacuations. This is because frequent falls obstruct evacuation activities and reduce overall evacuation efficiency.

(2) Altruistic behavior can aid collective activities, but the simulation results indicate that its benefits are not stable. Increasing the helping probability from 0.1 to 0.4 reduced evacuation time by half, demonstrating that increased helping behavior can significantly improve evacuation efficiency. However, when the help probability is greater than 0.4, evacuation time fluctuates with further increase in helping probability. This suggests that beyond a certain point, additional helping behavior does not provide practical benefits during evacuation.

(3) The range within which help is provided also affects evacuation time. The simulation results show that a help range of 0.5 m significantly increases the time required to evacuate all 400 people compared to other ranges. When the help range is greater than or equal to 0.7 m, the evacuation effect shows inconsistency. This indicates that help should be provided within a relatively close distance, as helping beyond a specific range does not necessarily improve overall evacuation time.

(4) Different demographic compositions also impact evacuation effectiveness. Groups with a larger elderly population showed weaker evacuation performance compared to those with more young and middle-aged individuals. This is due to two factors: the elderly group had a higher probability of falling and longer fall durations, which severely hindered evacuation progress, and they had limited ability to assist others, making it difficult to help evacuate from dangerous areas.

6. Conclusions

This study employs social force model to simulate the impacts of altruistic behavior and helping range on the evacuation efficiency. The study divides simulated evacuees into three age groups: young, middle aged, and aged groups. Simulations of each group was conducted and compared. The study also simulated three mixed age groups with different proportions of the age groups.

The study findings confirmed that evacuation efficiency is significantly affected by falling behavior more commonly associated with the aged group. That is, the increase of the proportion of aged people leads to the increase of evacuation time. However, the altruistic behavior has a positive effect on the evacuation process in general. The increase of the probability of altruistic behavior within a certain range (10% to 40%) will reduce the evacuation time. On average, the most reduction of evacuation time was achieved when the probability of help was 40%. That is to say, excessive altruistic behavior (more than 40% of probability to help) does not consistently reduce evacuation time. This is because multiple people scrambling to help a single fallen person can create more congestion. Finally, the study shows that help provided within the range of 0.7 m of the fallen person can greatly reduce the evacuation time. When the distance between helper and the fallen person is more than 0.7 m, the helper needs to cross the evacuation routes of other people, resulting in congestion and a prolonged evacuation time.

This study is important because it confirms that an excessive tendency to help others in a crowded emergency situation does not necessarily improve the entire evacuation process. A 40% willingness to help a fallen person nearby may provide a reference for training instructions. The help range of 0.7 m is also an interesting finding for training reference. However, considering the complexity of evacuation problems, it is difficult to implement simulation and evacuation effect analysis under multiple factors. Therefore, the research conclusion of this paper is given under idealized evacuation scenarios and abstract evacuation parameters, which excludes factors such as types of emergencies, psychological states of personnel and obstacles in evacuation scenarios that also have an impact on evacuation time. To some extent, these factors affect the accuracy of help probability and help range on evacuation time, which needs further research and exploration.

Future study should investigate how altruistic behavior affect evacuation time in different space boundaries. Current study is conducted in a simulated rectangular confined building structure. Different findings could be revealed if an open boundary space is used. The impact of exit layout can also be studied to maximize the effectiveness of emergency evacuation.

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Data availability: The program code and data that support the plots discussed within this paper is available from the corresponding author upon request.

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