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Impact of assistance behavior on evacuation efficiency in high-rise hospital inpatient buildings: An agent-based simulation study

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ABSTRACT

Hospital evacuations during emergencies present critical challenges given the mobility limitations of patients and shortages of healthcare personnel. This study investigates the role of social community assistance (e.g., visitors or caregivers) in enhancing evacuation efficiency under varying high-rise building heights (8, 16, 24, and 32 stories) and elevator availability. Through agent-based simulations, this paper systematically evaluates the impact of assistance ratios and assistance modes (proximity-based versus priority-based) on evacuation efficiency using Pathfinder. Results reveal a consistent principle regarding assistance ratio: intermediate assistance minimizes total evacuation time across all scenarios, with 50 % optimal for elevator-available buildings and 40 % ideal during elevator failures. Excessive assistance may create heterogeneous speed mismatches that cause moving bottlenecks in stairwells, while insufficient assistance leaves vulnerable groups stranded. For assistance modes, priority-based strategies reduce total evacuation time more effectively in elevator-available buildings by prioritizing upper-floor wheelchair users and avoiding long waiting times. Conversely, proximity-based approaches excel in stair-only evacuations by minimizing cross-floor inefficiencies. Furthermore, this study explores evacuation equity by analyzing the time of last evacuee for different vulnerable groups, demonstrating that optimized assistance strategies significantly reduce extreme delays for these groups across all building heights. These findings show that strategic mobilization of social communities can compensate for healthcare staff shortages while addressing ethical dilemmas in evacuation prioritization. These results provide actionable guidelines for optimizing hospital evacuation protocols, emphasizing adaptive strategies integrating real-time infrastructure status monitoring, dynamic assistance allocation, and community empowerment.

1. Introduction

Disaster response planning is crucial for reducing casualties and losses [1–3]. Not only natural disasters such as hurricanes, earthquakes, floods, landslides, and fires, but also some human-induced factors such as chemical leaks and terrorist attacks have made public facilities, including hospitals, face increasingly complex risks [4]. Globally, the vulnerability of healthcare facilities has become

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a significant issue [5]. For instance, in South American countries, more than 50 % of hospitals and primary healthcare institutions are located in high-risk areas [6]. Moreover, some historical events highlight the challenges hospitals face during emergencies. In the United States, Hurricanes Katrina and Rita led to the emergency evacuation of 58 hospitals, affecting more than 15,000 patients and healthcare workers [7]. In 2018, a hospital fire in South Korea resulted in the deaths of over 40 mobility-impaired patients [8]. Similarly, in 2021, a hospital in India suffered a power outage due to flooding, causing the deaths of dozens of critically ill patients who could not be transferred in time [9]. It can be seen that from all these incidents, the hospital emergency evacuation capabilities worldwide are tremendously inadequate. Therefore, the urgent need for in-depth research on the evacuation of people from hospital buildings requires further investigation.

The unique characteristics of hospital buildings present significant evacuation challenges due to the limited mobility of many patients, including those in intensive care, post-surgical recovery, and elderly populations, who face heightened vulnerability during emergencies because of physiological constraints (e.g., slow movement, reliance on assistive devices) and psychological stressors like panic behavior [10–12]. Compounding this issue is the critical shortage of professional healthcare personnel relative to patient numbers, which severely limits evacuation capacity during disasters [13]. To address this resource gap, some researchers have found the potential of mobilizing non-patient individuals within hospitals (visitors, caregivers, or organized community volunteers) as a strategy to enhance evacuation outcomes [14]. For example, exemplified by the well-known successful evacuation of Memorial Hermann Hospital in the United States, volunteer involvement significantly reduces casualties and improves overall evacuation efficiency [15,16]. Thus, effectively empowering social communities in hospitals as immediate assistants through preparedness initiatives could mitigate human resource shortages, optimize time-sensitive evacuations, and ultimately save more lives in hospital emergencies.

Currently, researchers have employed diverse computational models to address the complexities in hospital evacuation. Cellular automata (CA) models, for instance, efficiently simulate large-scale crowd movements through grid-based interactions, making them suitable for analyzing macroscopic evacuation patterns under spatial constraints [17,18]. Similarly, social force models excel in capturing microscopic physical interactions, such as pedestrian avoidance and congestion dynamics, in dense crowds [19]. However, these approaches struggle to represent the heterogeneity of hospital populations, where adaptive decision-making and dynamic assistance protocols require individualized behavioral logic. Agent-based modeling (ABM) has emerged as a superior framework for such scenarios, as demonstrated by Liu et al. (2024), who effectively simulated evacuations in elderly care facilities by modeling caregiver-patient interactions, assistive device dependencies, and ethical prioritization rules [20]. Unlike CA or social force models, ABM enables granular representation of agents' cognitive processes, spatial navigation, and real-time adaptation to environmental changes, which are the critical capabilities for studying the assistance behavior of the social communities [20,21].

Moreover, significant progress has been made in building evacuation research across multiple areas, including building design optimization, evacuation behavior simulation, and influencing factor analysis. In terms of building design, researchers have improved overall evacuation efficiency by optimizing building layouts, evacuation routes, and the configuration of safety facilities [22]. In evacuation behavior simulation, agent-based models like Pathfinder have been widely adopted to simulate crowd dynamics under diverse scenarios, providing scientific foundations for evacuation strategy development [23]. For instance, Zheng et al. [24] utilized simulations to investigate how building structures influence evacuation efficiency, proposing spatial optimization methods for route planning. Meanwhile, factor analysis research has identified key determinants of evacuation performance, including crowd density, exit width, emergency lighting conditions, and psychological factors such as panic and herd behavior [25]. To systematically review current studies, Table 1 synthesizes studies selected through a structured framework prioritizing (1) methodological alignment with simulation-driven evacuation research, (2) focus on vulnerable populations (e.g., pediatric, geriatric), and (3) relevance to high-rise hospital building contexts.

As evidenced by the methodologies of building evacuation studies in Table 1, simulation tools like Pathfinder have become a cornerstone for modeling crowd dynamics and assisted behaviors [22,28]. However, this study identifies three unresolved challenges specific to high-rise hospital evacuations: (1) most studies overlook the systemic impacts of fluctuating assistance ratios under real-world staff shortages, relying instead on fixed assistance assumptions [28] (2) While most models adopt static priority rules (e.g., uniformly evacuating wheelchair users first); without evaluating context-specific trade-offs [22,34], recent work [20] proposes a

Table 1
Key studies on healthcare facility evacuations.

Serial Number	Building Type	Research Focus	Research Method
[13]	Hospital	Evacuation parameters for persons	Survey & Interview
[20]	Elderly care facilities	Disabled older adults evacuation	Simulation
[22]	Geriatric hospital	Stratified evacuation	Simulation
[26]	Maternity & children's hospital	Evacuation strategy analysis	Simulation
[27]	Hospital	Egress safety criteria	Survey
[28]	Hospital	Nurses' assistance behavior	Simulation
[29]	General Hospital	Evacuation including wheelchairs	Cellular automata
[30]	Hospital	Fire evacuation training	VR
[31]	Pediatric Hospital	Group evacuation	Simulation
[32]	Hospital	Agent-based evacuation modeling	Simulation
[33]	Hospital registration hall	Crowd evacuation behavior	Simulation
This Paper	Hospital inpatient building	Assistance behavior	Simulation

dynamic prioritization framework that aligns closely with healthcare needs. Their conceptual basis for assisted evacuation modeling directly informs our critique of current limitations; (3) The debate on optimal assistance ratios remains unresolved, particularly when balancing urgency (e.g., patients with wheelchairs) against fairness (e.g., equitable access to limited caregivers). To resolve these limitations, our study introduces a simulation framework that combines spatial modeling of agent interactions with adaptive decision-making protocols (derived from steering mode algorithms), with technical foundations of which are rigorously detailed in Section 2.

Additionally, traditional evacuation strategies mainly rely on stairways, this approach proves insufficient in high-rise hospitals during emergencies. Studies have shown that the appropriate use of elevators can significantly enhance evacuation efficiency, especially when evacuating vulnerable groups [35–37]. For instance, during a fire in 2018, the Shanghai World Financial Center successfully utilized emergency elevators to transfer individuals with mobility impairments, preventing further casualties [38]. However, existing studies often lack systematic analysis of how to optimally integrate elevators with stairway usage under varying building scenarios, also overlooking the chaos that arises in the absence of guided assistance protocols. Furthermore, reliance on different evacuation strategies varies across buildings of different heights, given that high-rise buildings require coordination of vertical evacuation, while low-rise buildings are more prone to stairway congestion [39]. Therefore, building height and elevator availability represent critical, underexplored contextual factors influencing evacuation efficiency.

Given the research gaps identified above, this study focuses on the emergency evacuation of hospital inpatient buildings and examines the impact of assistance behavior on evacuation efficiency. Specifically, the purpose of this paper is to investigate the optimal assistance strategy for the social community in the hospital, so that to address the insufficiency of professional healthcare personnel. Pathfinder software is utilized in this study to simulate different scenarios involving varying assistance ratios, assistance modes, building heights, and elevator availability. This study primarily evaluates the following aspects: (1) The impact of different assistance ratios on evacuation time; (2) The effect of different assistance modes on evacuation efficiency (3) The influence of various building conditions (e.g., floor height, elevator availability); on evacuation efficiency. The findings of this study can provide practical support for optimizing emergency evacuation strategies in hospital inpatient buildings, improving evacuation procedures, and informing the design of future intelligent evacuation systems to minimize casualties and property losses during disasters.

The remainder of this paper is structured as follows: Section 2 introduces the methodologies and modeling information; Section 3 describes the results and analysis among different scenarios; Section 4 concludes this paper and provides some policy implications.

2. Methods and materials

2.1. Simulation methodology

This study employs Pathfinder software, a high-resolution agent-based simulation platform, to model emergency evacuation processes in high-rise hospital inpatient building scenarios. By setting the evacuees' body and speed parameters, Pathfinder can simulate the evacuation process by defining the Interaction Coefficient (α) and Attraction Coefficient (β) among individuals to optimize their path selection and enhance evacuation efficiency [40,41].

Compared to traditional path-planning methods, the Pathfinder Optimization Algorithm (POA) exhibits greater flexibility and

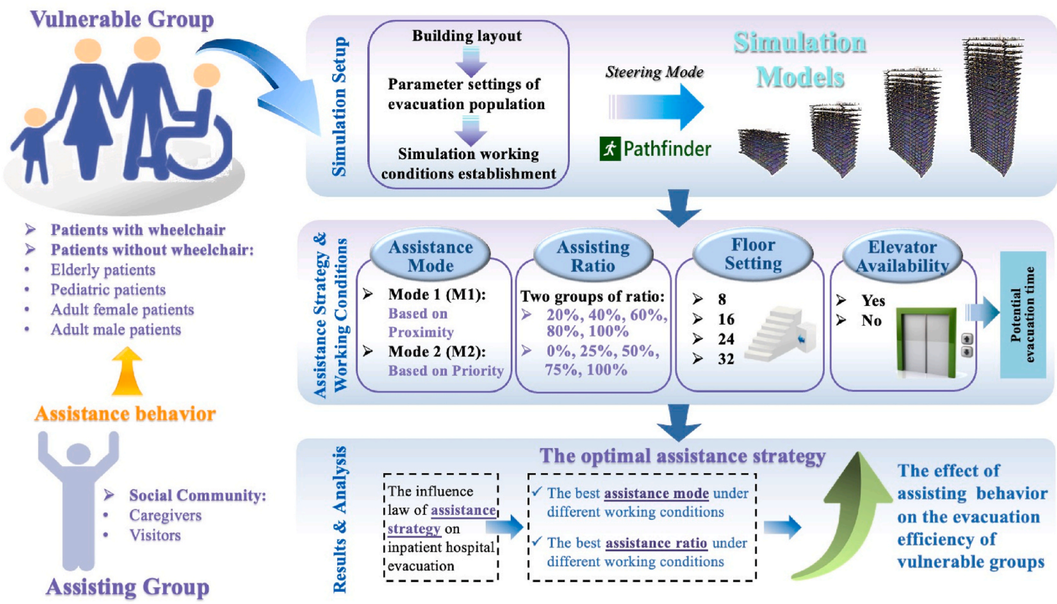

Fig. 1. Technology roadmap of this study.

adaptability. In complex environment like hospitals, individuals need to continuously adjust their movement direction based on real-time information, avoid collisions with others, and identify the optimal path within the shortest possible time. Therefore, this software can meet the needs of this research to a large extent. The work frame of the whole paper is illustrated in Fig. 1 below.

2.1.1. *Agent-based simulation framework*

The position of each agent in POA is iteratively updated to identify a more efficient movement path [22,40,42]. The mathematical expression is as follows:

$$X_i^{(k+1)} = X_i^{(k)} + \alpha r_1 \left(X_j^{(k)} - X_i^{(k)}\right) + \beta r_2 \left(X_j^{(k)} - X_i^{(k)}\right) + A \tag{1.}$$

where $X_i^{(k)}$ is the position vector of individual i at the k th iteration, $X_j^{(k)}$ is the position vector of neighboring individual j at the k^{th} iteration, and r_1, r_2 are random variables within $[0,1]$ representing stochastic influence in the interaction process. The parameter α is the interaction coefficient that controls the degree of attraction toward neighboring individuals, while β is the attraction coefficient determining the degree of movement toward the global optimal position. The perturbation term A introduces randomness to enhance exploration within the search space.

Specifically, the perturbation term A ensures that individuals have higher exploratory tendencies in the early stages, while gradually stabilizing as iterations increase, thereby improving algorithm convergence. And is computed as follows:

$$A = \left(1 - \frac{k}{k_{max}}\right) u_1 D_{ij} \tag{2.}$$

where k is the current iteration count, and k_{max} is the maximum number of iterations. $D_{ij} = \|X_i - X_j\|$ denotes the Euclidean distance between individuals i and j, and u_1 is a random variable in the range $[-1,1]$ introducing uncertainty. In the meantime, as k increases, A gradually decreases, which ensures a better convergence in later iterations.

Furthermore, the POA employs a Pathfinder agent mechanism, where the movement state of each agent depends on its historical trajectory and is influenced by the perturbation term to avoid local optima during evacuation. The formulation is as follows:

$$X_p^{(k+1)} = X_p^{(k)} + 2r_3 \left(X_p^{(k)} - X_p^{(k-1)}\right) + A \tag{3.}$$

where $X_p^{(k)}$ represents the position of the pathfinder agent at the k th iteration, r_3 is a random variable in the range $[0,1]$, and A is a perturbation term calculated as follows:

$$A = u_2 e^{-2k/k_{max}} \tag{4.}$$

where u_2 is a random variable within $[-1,1]$, used to control the exploration behavior of the pathfinder agent.

In Pathfinder, there are two behavior modes: SFPE (Society of Fire Protection Engineers) and Steering mode [40]. The SFPE mode employs simplified engineering assumptions with fixed parameters (e.g., uniform 1.1 m/s walking speed) and flow-based calculations aligned with fire protection standards, prioritizing computational efficiency for code-compliance evaluations. Conversely, the Steering mode utilizes agent-based autonomous navigation with continuous collision avoidance and dynamic pathfinding, enabling granular modeling of heterogeneous populations through individualized speed profiles, anxiety modifiers, and social interactions. Therefore, Steering mode is selected in this study due to its support for dynamic agent behavior and individualized motion profiles.

The Steering mode enables individuals to adjust paths based on environmental factors. Speed and acceleration are calculated as:

$$v_d(D) = v_{max} \times \frac{0.85 \times k}{1.19} \tag{5.}$$

where $v_d(D)$ is the target speed, v_{max} is the maximum speed and k is an adjustment factor for terrain types.

$$a_{max} = \frac{v_{max}}{t_{accel}} \tag{6.}$$

where a_{max} is maximum acceleration and t_{accel} is the acceleration time.

Meanwhile, the best direction is chosen based on path weight S_c is measured by:

$$S_c = \frac{\theta}{2\pi} \tag{7.}$$

where θ is the angle between the current direction and the path curve.

2.1.2. *Assistance interaction behavioral framework*

To simulate realistic evacuation assistance in hospital inpatient building, this study designed a behavioral framework formalizing six sequential interaction stages between social communities (assisting agents) and mobility-impaired patients (assisted agents), as systematized in Table 2 below. This staged approach aligns with empirical findings on emergent cooperation in evacuations [43–45], where structured collaboration optimizes efficiency despite competitive pressures.

These stages systematically transition from independent navigation to assistance initiation, physical pairing, guided movement, and post-assistance autonomy restoration. Combined with Pathfinder's built-in algorithms and Steering mode, this staged framework explicitly models time-delayed pairing bottlenecks, speed-dependent congestion emergence, and context-dependent detachment behaviors unique to evacuations in hospital inpatient buildings, ensuring behavioral fidelity throughout evacuation assistance.

2.2. Simulation setup

2.2.1. Main assumptions

To simplify the model and focus on key research points, several assumptions have been made for this paper. Firstly, all wheelchair users cannot navigate stairs independently until being assisted by others. Secondly, pre-existing social relationships (e.g. kinship and companionship) and group psychology effects like herd mentality and panic propagation are not considered. Thirdly, evacuation is assumed to trigger an immediate response, with preparation phases such as reaction time omitted. Lastly, dynamic hazard progression, including fire spread and structural collapse, is not modeled.

2.2.2. Building information

The simulation study is conducted based on a high-rise inpatient building of a large tertiary hospital located in Southwest China, with its inner architectural layout illustrated in Fig. 2 below. The hospital's design adheres to the Chinese Code for Design of General Hospital (GB 51039-2014), ensuring alignment with representative high-rise hospital configurations [46]. The specific structural parameters include: (1) The first-floor lobby contains 28 beds, while each floor from the second floor onward accommodates 60 beds. (2) The hospital building is equipped with two stairwells and two elevators for vertical evacuation; evacuees can freely choose any exits. (3) To systematically examine the impact of building height and population scale on optimal assisting strategies, four configurations are tested: 8, 16, 24, and 32 stories (as illustrated in Fig. 3), covering high-rise (8 and 16 floors) to ultra-high-rise hospital inpatient buildings (24 and 32 floors).

Specifically in real-world evacuation scenarios, for the two elevators in the building, elevators may remain operational with the steps shown in Fig. 4, yet become hazardous or inoperative during fire incidents or seismic events due to power supply failures or structural damage. To address this critical situation, our study systematically incorporates elevator operational status as a binary variable (available/unavailable) in hospital evacuation modeling. The elevator system parameters, followed by the international building codes of emergency evacuation mode (EVAC), are provided in Table 3 below [40].

Based on the information above, Table 4 illustrates all different hospital inpatient building evacuation working conditions considered in this study (i.e. eight distinct hospital simulation models). The working conditions are designed based on two key factors: hospital building height (8, 16, 24, and 32 stories) and the availability of elevators (available/unavailable).

2.2.3. Occupant profiles

The hospital evacuation population comprises two distinct groups with divergent mobility characteristics: (1) vulnerable group including patients that require assistance, and (2) assisting group of visitors and caregivers that can provide evacuation assistance. Based on anonymized demographic records from a tertiary hospital in Southwest China and nationally recognized healthcare staffing guidelines, vulnerable group are stratified into four mobility-challenged categories (geriatric: 40 %, adult male: 20 %, adult female: 20 %, pediatric: 20 %), with 25 % of each being wheelchair-dependent, that aligned with mobility aid utilization patterns in Chinese hospitals [47]. The assisting group, set at a 0.95:1 ratio to patients, reflects China's 2023 action plan for nursing service optimization [48] and regional visitor availability during peak hours. Anthropometric and kinematic parameters are adopted from studies on hospital evacuation dynamics [47], where level walking speed explicitly denotes movement velocity on completely horizontal surfaces (e.g., corridors, rooms), and stair traversal speed represents the actual velocity vector along the inclined path of stairs during ascent or descent. All parameters are comprehensively summarized in Table 5 below.

Based on the estimating and calculating methods introduced above, Table 6 details the total evacuee counts per occupant type across four hospital buildings with different stories.

Table 2
Staged assistance behavioral logic.

Stage	Interactive behavior description	Key behaviors set in Pathfinder
Stage I	Agents initialize with independent navigation profiles	Set profile property (speed attributes); Go to waypoint; Go to exit(s)
Stage II	Assisted agents signal need; assisting agents scan and evaluate requests based on proximity/priority match	Add tag ("Assistance_Needed"); Wait for assistance by assisted evacuation team (s)
Stage III	Assisting agents approach and form physical groups; collision avoidance auto-positions agents	Go to occupant; Assist occupants; Create trigger (group anchor point)
Stage IV	Assisted agents maintain optimal distance to assistants' anchor point using Pathfinder's follower mechanics	Go to current trigger (inherits Pathfinder's follower velocity handling); Wait for amount of time (separation recovery)
Stage V	Group detachment upon reaching safety; original navigation restored	Remove tag; Detach from assistants; Destroy trigger
Stage VI	Agents resume independent egress	Go to exit(s)

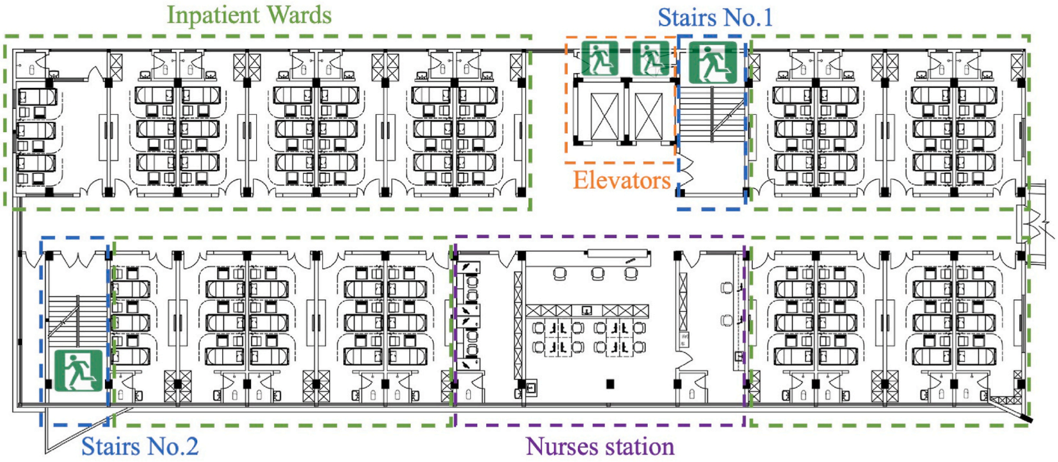

Fig. 2. The general layout of the hospital inpatient building's interior.

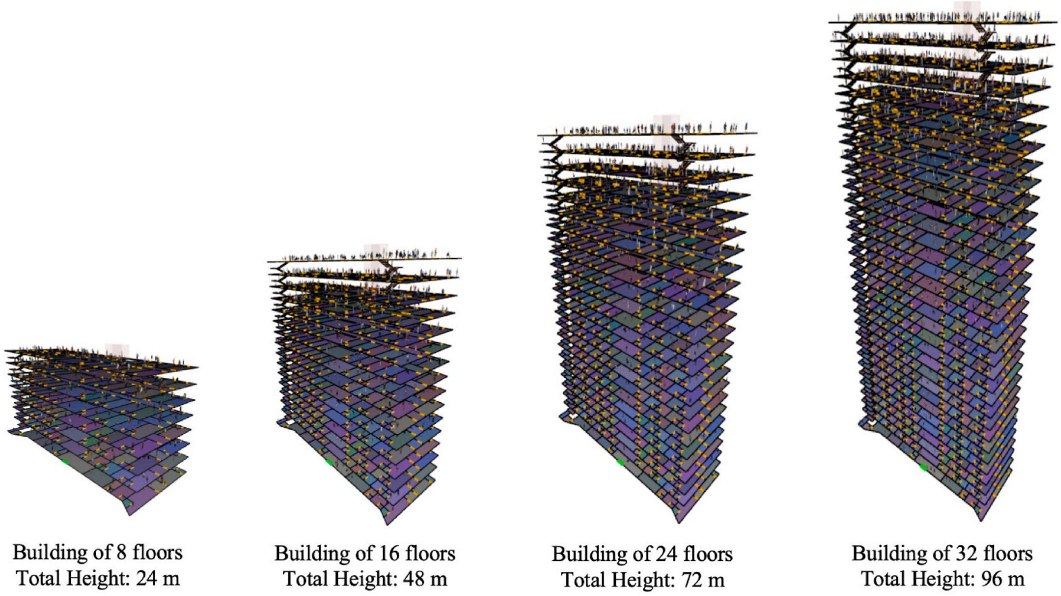

Fig. 3. Four hospital inpatient building types with different heights.

2.3. Assistance strategy

Effective assistance strategies are essential for the assistance behavior in hospital evacuation. This paper investigates two interdependent parameters: assistance ratios and assistance modes. This methodological framework aims to systematically evaluate how distinct assistance strategies of the assisting group influence evacuation time for mobility-impaired populations.

2.3.1. Assistance ratio

As introduced in Section 2.2, the availability of elevators (can or cannot be used) is discussed in this study. In each case, we further examined the optimal assistance ratio in the assisting group. When elevators are available, the assistance ratio was set at 0 %, 25 %, 50 %, 75 %, and 100 %. However, for conditions that elevators cannot be operated, given wheelchair users are unable to evacuate independently and had to rely on assistance, so the assistance ratio is set starting at 20 % to make sure all evacuees can succeed in surviving, followed by 40 %, 60 %, 80 %, and 100 %.

2.3.2. Assistance mode

In this paper, there are mainly two assistance modes considered as the behavioral protocols for the assisting group, building upon the conceptual basis for assisted evacuation modeling established by Liu et al. (2024) [20]. These modes are designed to address

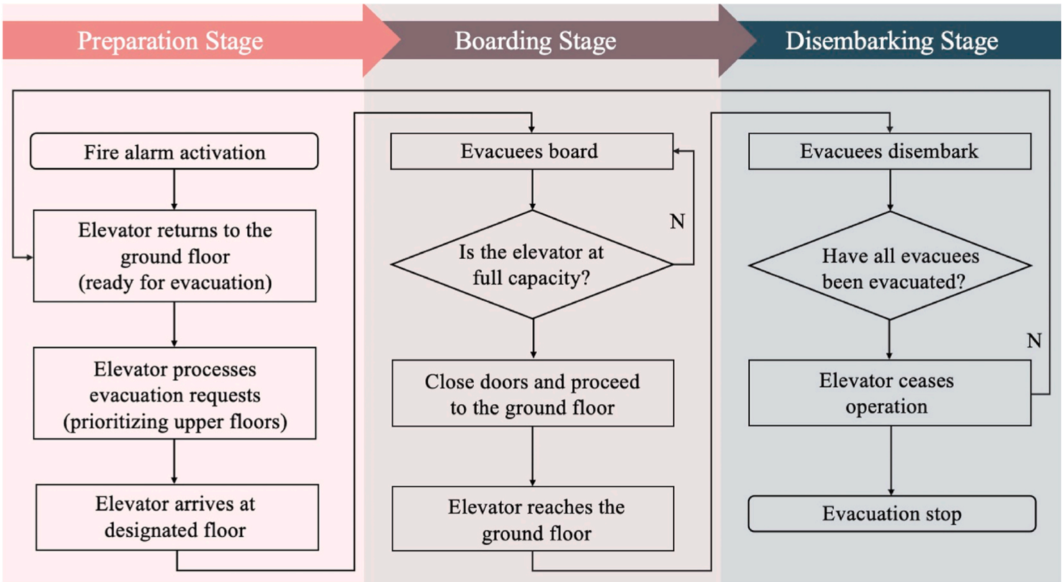

Fig. 4. Flow chart of the elevator operation during the evacuation.

Table 3
Parameter settings of elevator operation - EVAC.

Parameter	Value Setting
Nominal Load	20 persons
Open Delay	5.0 s
Close Delay	5.0 s
Initial Floor	0.0 m
Call Distance	0.5 m
Floor Priority	Top-down

Table 4
Summary of building working conditions.

Working conditions	Total stories	Availability of elevators
C1-1	8	Yes
C1-2	8	No
C2-1	16	Yes
C2-2	16	No
C3-1	24	Yes
C3-2	24	No
C4-1	32	Yes
C4-2	32	No

Table 5
Anthropometric and kinematic parameters of different hospital occupants.

Parameter Type	Shoulder width (m)	Height (m)	Level walking speed (m/s)	Stair traversal speed (m/s)
Adult female (including caregivers and visitors)	0.45	1.60	1.03	0.90
Adult male (including caregivers and visitors)	0.52	1.70	1.15	1.01
Elderly patients	0.48	1.65	0.50	0.45
Adult female patients	0.45	1.60	0.85	0.75
Adult male patients	0.52	1.70	1.00	0.90
Pediatric patients	0.40	1.40	0.60	0.54
Wheelchair patient	–	1.00	1.00	–

Table 6
Occupant distribution across different simulated hospital configurations.

Number of floors	Total hospital beds	Total number of evacuees	Wheelchair patients	Elderly patients	Adult female patients	Adult male patients	Pediatric patients	Caregivers and visitors
8	448	660	85	102	51	51	51	320
16	928	1360	175	210	105	105	105	660
24	1408	2060	265	318	159	159	159	1000
32	1888	2770	355	426	213	213	213	1350

unresolved theoretical debates in hospital evacuation literature, particularly the tension between efficiency-driven and ethics-driven prioritization [49]. Specific introductions of the two different assistance modes are illustrated in Fig. 5 and described below.

(1) Assistance mode 1 (M1): Assistance based on proximity

This mode guides the assisting group to prioritize assisting those who are geographically closest to them, aligning with strategies emphasizing rapid response efficiency to maximize resource utilization under time constraints [50]. The primary goal of this strategy is to reduce response time, an approach supported by Johnson's principle of optimizing evacuee throughput during emergencies, while ensuring broader coverage of vulnerable groups [50].

(2) Assistance mode 2 (M2): Assistance based on priority

This mode guides assisting the group to prioritize assistance based on the mobility-impaired level of specific population groups. The priority order is as follows: wheelchair patients, elderly patients, pediatric patients, adult female patients, and adult male patients. The priority order reflects ethical frameworks advocating for populations with the least self-rescue capacity, as proposed by Rabbani et al. [51]. When help providers receive requests, they first determine whether the individuals belong to these priority groups and then allocate assistance accordingly. The aim of this strategy is to ensure that the most vulnerable populations can receive timely assistance.

Above all, considering the two different assistance modes and assistance ratios, a total of 20 assistance strategies (shown in Table 7 below) are tested in this study. Given that the spatial arrangement of all occupants may influence the overall evacuation efficiency, to account for this variability, all individuals in this study are randomly distributed throughout the building prior to running each simulation. For each experimental scenario with its corresponding assistance strategy, 15 independent simulations are conducted with regenerated initial positions for all occupants, ensuring robust evaluation of hospital evacuation performance across diverse spatial configurations.

3. Results and analysis

3.1. Overall simulation results and key influencing factors

In this study, Total Evacuation Time (TET) calculated by Pathfinder software serves as the primary metric to evaluate different assistance strategies' efficiency. First of all, to systematically identify critical factors influencing TET and establish actionable optimization principles, Spearman's Rho correlation analysis was adopted. This non-parametric method was selected due to its compatibility with the dataset, which includes a mix of continuous variables (e.g., TET, occupant number) and ordinal discrete variables (e.g., assistance modes ranked by intervention intensity) [52]. Unlike Pearson's correlation, Spearman's Rho does not assume linearity or normality, making it suitable for detecting monotonic relationships—such as whether increasing elevator usage consistently reduces evacuation time, even if the rate of reduction varies nonlinearly [53,54].

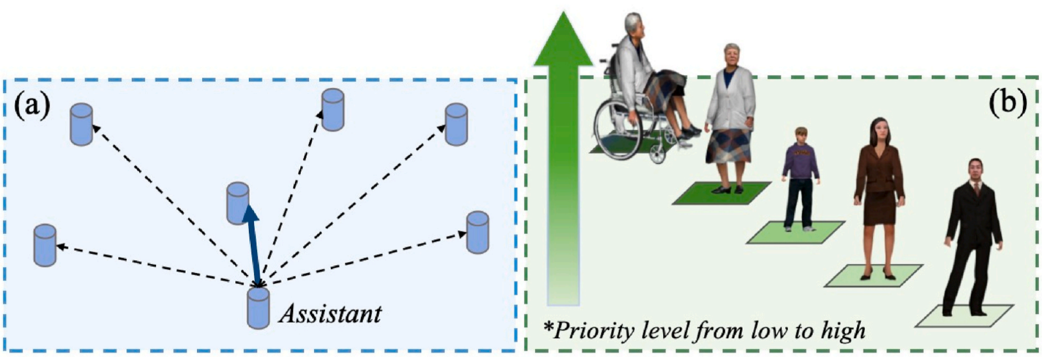

Fig. 5. Illustration of the assistance mode based on (a) proximity and (b) priority.

Table 7
Twenty assistance strategies considered in this study.

Elevators available			Elevators unavailable		
Assistance strategy	Assistance mode	Assistance ratio	Assistance strategy	Assistance mode	Assistance ratio
M1-0 %	M1	0 %	M1-20 %	M1	20 %
M1-25 %	M1	25 %	M1-40 %	M1	40 %
M1-50 %	M1	50 %	M1-60 %	M1	60 %
M1-75 %	M1	75 %	M1-80 %	M1	80 %
M1-100 %	M1	100 %	M1-100 %	M1	100 %
M2-0 %	M2	0 %	M2-20 %	M2	20 %
M2-25 %	M2	25 %	M2-40 %	M2	40 %
M2-50 %	M2	50 %	M2-60 %	M2	60 %
M2-75 %	M2	75 %	M2-80 %	M2	80 %
M2-100 %	M2	100 %	M2-100 %	M2	100 %

The results revealed statistically significant correlations between all examined variables and TET as shown in Table 8 below. Floor number and occupant number exhibited the strongest positive correlations, highlighting the inherent challenges of evacuating multi-story hospitals with high patient density. Conversely, elevator availability and assistance ratio showed significant negative correlations, underscoring the potential of resource allocation (e.g., prioritizing elevator access for vulnerable groups) and coordinated assistance behaviors to mitigate delays. The weaker but still significant negative correlation of assistance mode further emphasized the value of protocol standardization, such as tiered prioritization for patients with differing mobility needs.

These findings achieve two critical objectives. Firstly, they quantify unavoidable bottlenecks imposed by fixed architectural and demographic factors, such as building height and occupant load. Secondly, they prioritize adjustable variables, such as elevator utilization and assistance strategy, as practical levers for optimizing evacuation efficiency. Similarly, advocating social community to dynamically adjust assistance ratios (Section 3.2) or involvement in evacuation tasks with different modes (Section 3.3) may further affect evacuation efficiency. By linking simulation outcomes to statistically validated relationships, this analysis provides a framework for hospitals to balance structural limitations with adaptive operational strategies, ultimately enhancing evacuation safety in high-risk environments.

3.2. *Influence of assistance ratio on evacuation efficiency*

The assistance ratio, defined as the proportion of assisting group individuals (visitors and caregivers) actively engaged in supporting mobility-impaired occupants, plays a critical yet context-dependent role in influencing evacuation outcomes, as demonstrated by simulations under two distinct scenarios: elevator-enabled and elevator-disabled conditions.

3.2.1. *Scenario 1: elevators available*

When elevators are functional, the relationship between assistance ratio and TET follows a U-shaped distribution, with TET minimized at intermediate ratios shown in Fig. 6. At low assistance ratios (0–25 %), insufficient assistance leads to severe bottlenecks for wheelchair users on upper floors (Fig. 7 (a)). With limited assistants, many wheelchair-bound occupants remain stranded near elevator bays, unable to navigate independently to evacuation points. This delay propagates across floors, as elevators cycle repetitively to evacuate densely clustered wheelchair users, thereby prolonging overall TET significantly.

Conversely, at excessively high assistance ratios (75 %–100 %), the over-deployment of social communities to assist wheelchair users or disabled people creates systemic inefficiencies. When assistants accompany wheelchair-bound occupants in stairwells, their movement speed is significantly reduced due to the physical constraints of navigating stairs with mobility aids. This creates heterogeneous groups, composed of assistants and assisted individuals, that travel at speeds 40–60 % slower than independent evacuees [55]. In narrow staircases (1.6 m width), these groups occupy disproportionate space, forming moving bottlenecks that obstruct faster-moving individuals [56,57]. Consequently, even as vulnerable populations receive ample assistance, the slowed progression of assisted pairs propagates congestion across floors, delaying the evacuation of otherwise independent occupants (Fig. 7 (b)). Essentially, the well-intentioned increase in assistance backfires: efforts to assist vulnerable groups unintentionally hinder the broader population's ability to evacuate swiftly.

Table 8
Spearman's Rho correlation analysis results.

Variable	Correlation Coefficient	p-value	Significance ($p < 0.01$)
Assistance mode	−0.2240	1.12×10^{-6}	Yes
Assistance ratio	−0.5323	7.11×10^{-9}	Yes
Elevators availability	−0.7242	1.10×10^{-15}	Yes
Floor number	0.8622	1.20×10^{-25}	Yes
Occupant number	0.8871	1.20×10^{-25}	Yes

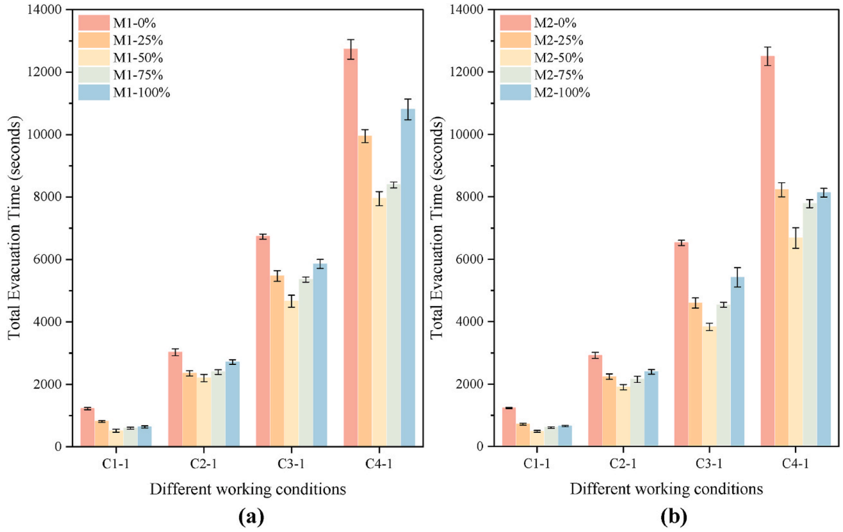

Fig. 6. TET results among different assistance ratios when elevators are available. (a) M1: Assistance based on proximity, and (b) M2: Assistance based on priority.

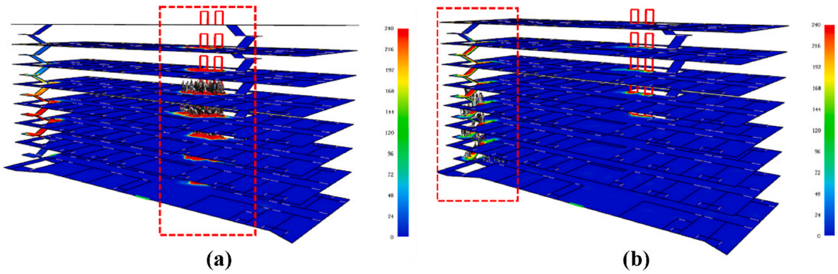

Fig. 7. Evacuation bottleneck happened with (a) low and (b) high assistance ratio.

3.2.2. Scenario 2: elevators unavailable

In elevator-disabled scenarios, the relationship shifts to a V-shaped distribution as shown in Fig. 8, with TET minimized at moderate ratios (40 %). At low assistance ratios (20 %), the scarcity of assistants forces vulnerable individuals to wait indefinitely for aid, severely delaying their progress. Wheelchair users, in particular, face insurmountable barriers without assistance, leading to gridlock in stairwells. At high ratios (80 %–100 %), however, excessive assistance allocation exacerbates congestion as well due to the inherent speed mismatch between heterogeneous groups. When large numbers of social communities assist vulnerable groups in narrow staircases, the movement of these pairs is constrained by the slower member's pace. This creates "speed harmonics" where fast-moving independent evacuees are trapped behind slower heterogeneous groups, amplifying bottlenecks.

In both cases when elevators are available or unavailable, the optimal middle-level assistance ratio under both M1 and M2 mitigates these extremes. At this level, assistants sufficiently support vulnerable groups without overwhelming stairwell capacity. For example, M1 ensures decentralized assistance across floors, preventing localized congestion, while M2 prioritizes aid to individuals on critical upper floors without over-concentrating assistants. This balance reduces the likelihood of both stairwell blockages or elevator waiting, while ensuring vulnerable populations receive timely support.

3.3. Influence of assistance mode on evacuation efficiency

While the role of the assistance ratio has been discussed, the relative superiority of the two assistance modes is still contingent on infrastructure conditions. Specifically, the choice between proximity (M1) and priority (M2) assistance modes introduces trade-offs in evacuation pathway utilization and bottleneck management, which manifest differently depending on elevator functionality. In this section, this paper further dissects how elevator availability affects the effectiveness of these modes, revealing a finding with critical implications for context-dependent strategy design.

3.3.1. Scenario 1: elevators available

When elevators are available, M2 generally outperforms M1 in all high-rise buildings (depicted in Fig. 9). By prioritizing

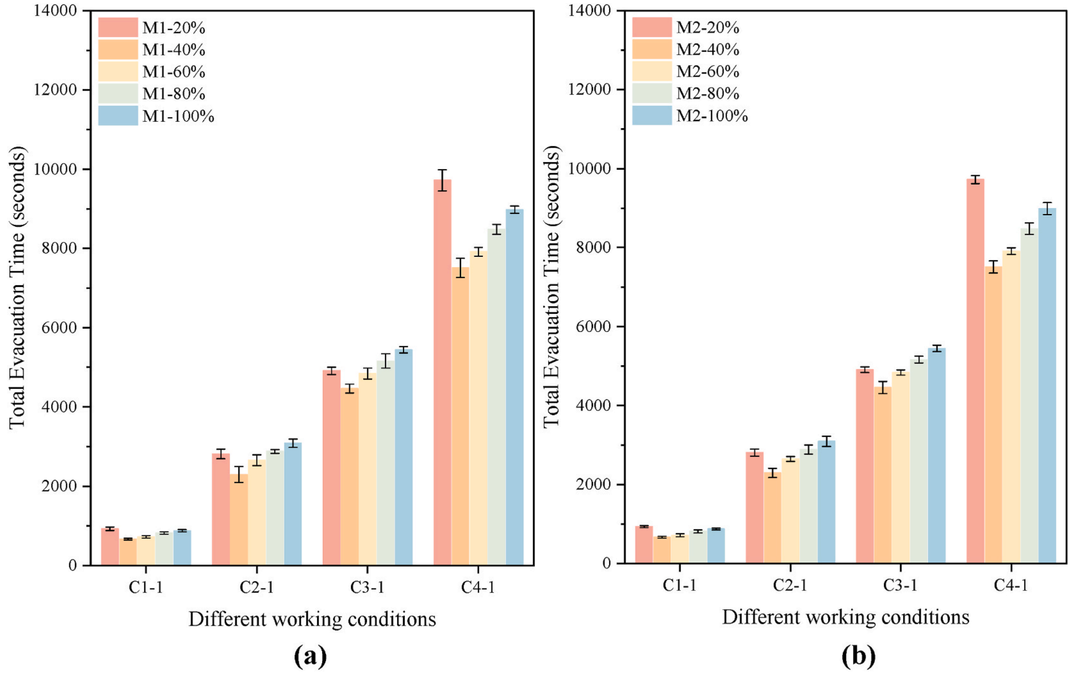

Fig. 8. TET results among different assistance ratios when elevators are unavailable. (a) M1: Assistance based on proximity, and (b) M2: Assistance based on priority.

wheelchair users on upper floors for early elevator access, M2 reduces critical bottlenecks in elevator lobbies. For instance, in 32-story simulations, M2 maintains elevator lobby densities at 1.6 persons/m^2 (below the safety threshold of 2.0 persons/m^2), whereas M1 allows densities to peak at 2.8 persons/m^2, exacerbating delays. This prioritization aligns with natural evacuation dynamics: assisting individuals to evacuate via stairs 1.2–1.5 times faster than via elevators, creating efficient evacuation without overloading either pathway. In contrast, M1 fails to address the disproportionate demand on upper floors, resulting in prolonged elevator cycles and stair underutilization, especially in 24 and 32 stories buildings.

However, in lower-rise buildings (8 and 16 floors), the performance gap between M1 and M2 narrows. Shorter elevator cycles (<90 s) inherently mitigate congestion, reducing the urgency for prioritization. Here, both modes achieve comparable TET, as elevator capacity suffices to accommodate demand even under M1's decentralized approach.

3.3.2. Scenario 2: elevators unavailable

When elevators are unavailable, M1 proves superior due to the rigid constraints of narrow staircases as shown in Fig. 10 below. M2's prioritization logic, while theoretically beneficial, inadvertently exacerbates congestion. Assistants under M2 often traverse multiple floors to assist high-priority individuals, increasing travel distances and stairwell occupancy times. For example, in 24-floor simulations, M2 increases average stairwell dwell time by 22 % compared to M1, as assistants navigate vertically to reach designated recipients. This extended occupancy amplifies congestion, particularly in chokepoints like stair landings.

M1's decentralized strategy minimizes inefficiencies in elevator-disabled scenarios by spatially constraining assistance tasks to the immediate vicinity of assistants, thereby eliminating unnecessary vertical movement. In practice, this means social communities assist individuals on the same floor or adjacent floors, rather than traversing multiple levels to reach high-priority recipients as required by M2. By localizing assistance, M1 reduces stairwell occupancy durations (critical in narrow, single-pathway evacuations) where extended dwell times directly correlate with congestion escalation. For instance, in 24-floor simulations, M2's prioritization logic increased average stairwell dwell time by 22 % compared to M1, as assistants frequently crossed 3 to 5 floors to reach designated individuals, occupying limited stair space for prolonged periods.

Furthermore, M1 mitigates the inherent speed mismatch within heterogeneous groups. When assistants pair with mobility-impaired individuals, the group's pace synchronizes with the slowest member, a phenomenon termed speed harmonization [58]. In M2, prioritization exacerbates this mismatch: assistants traveling longer distances create intermittent "slow-moving clusters" that obstruct faster evacuees (moving at 1.0–1.2 m/s), triggering cascading delays. M1 circumvents this by dispersing heterogeneous groups across floors, preventing localized clustering. This dispersion ensures a steadier flow, as slower groups do not persistently block the same stair segments.

Critically, M1's simplicity aligns with the physical reality of stairwell evacuations. Complex prioritization schemes like M2 require real-time coordination and vertical mobility—both infeasible in crowded, chaotic environments. M1's proximity-based approach operates effectively without centralized oversight, making it inherently robust under stress. Thus, in elevator-disabled scenarios, where evacuation pathways are singular and capacity-constrained, M1's localized efficiency outweighs the theoretical benefits of M2's

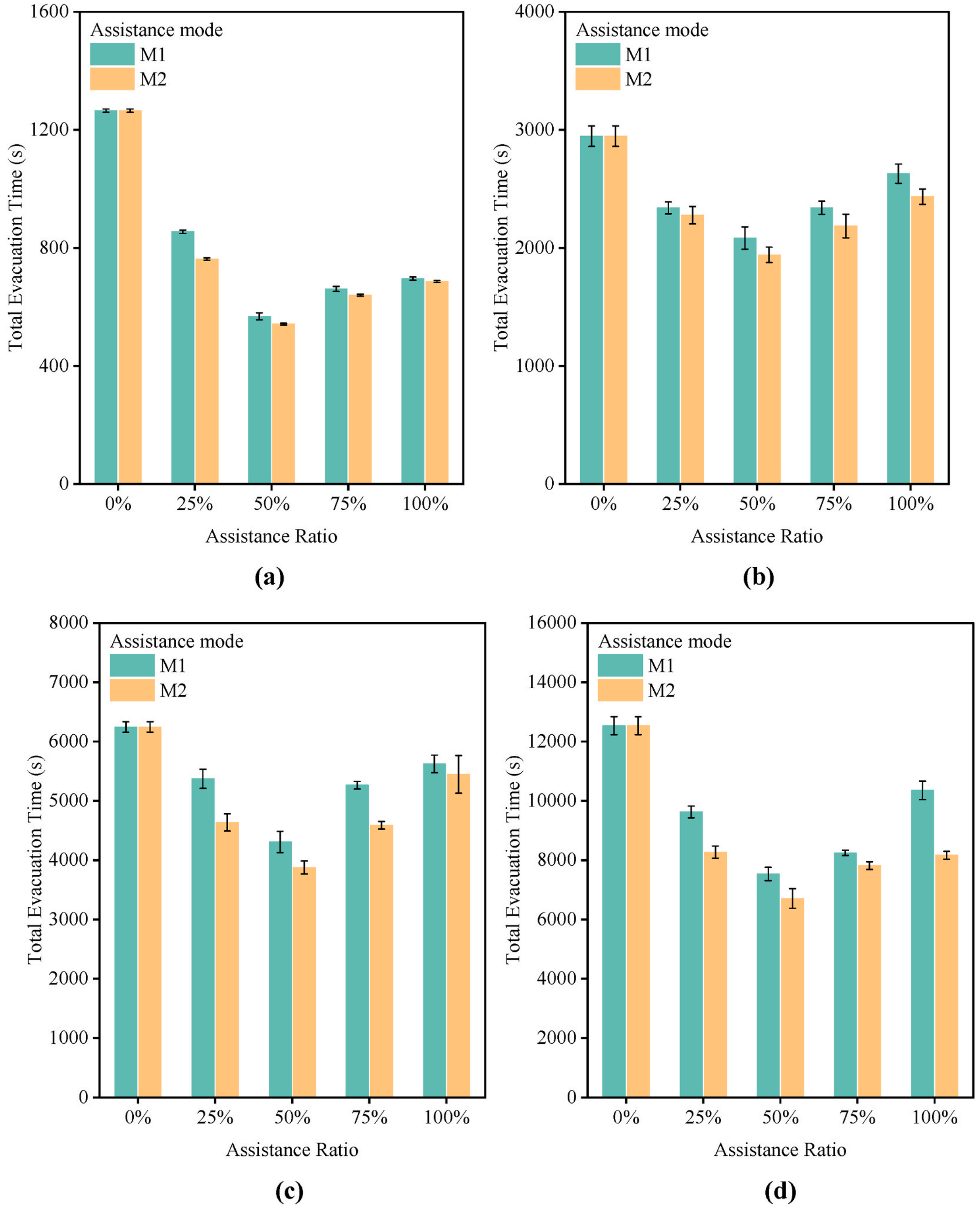

Fig. 9. TET results among different assistance modes when elevators are available in (a) 8 stories, (b) 16 stories, (c) 24 stories and (d) 32 stories.

targeted prioritization.

Above all, these findings advocate for infrastructure-aware mode selection. In elevator-enabled high-rises, M2's prioritization optimizes elevator-stair synergy, whereas M1's decentralized approach excels in elevator-disabled or low-rise contexts. Table 9 below summarizes the optimal assistance strategy in different building scenarios. Hospitals should implement dynamic mode-switching protocols: deploying M2 during functional elevator conditions to alleviate upper-floor bottlenecks, and reverting to M1 during outages to prevent stairwell gridlock. This adaptability ensures that evacuation strategies remain responsive to both architectural constraints and real-time operational status, ultimately enhancing safety across diverse emergency scenarios.

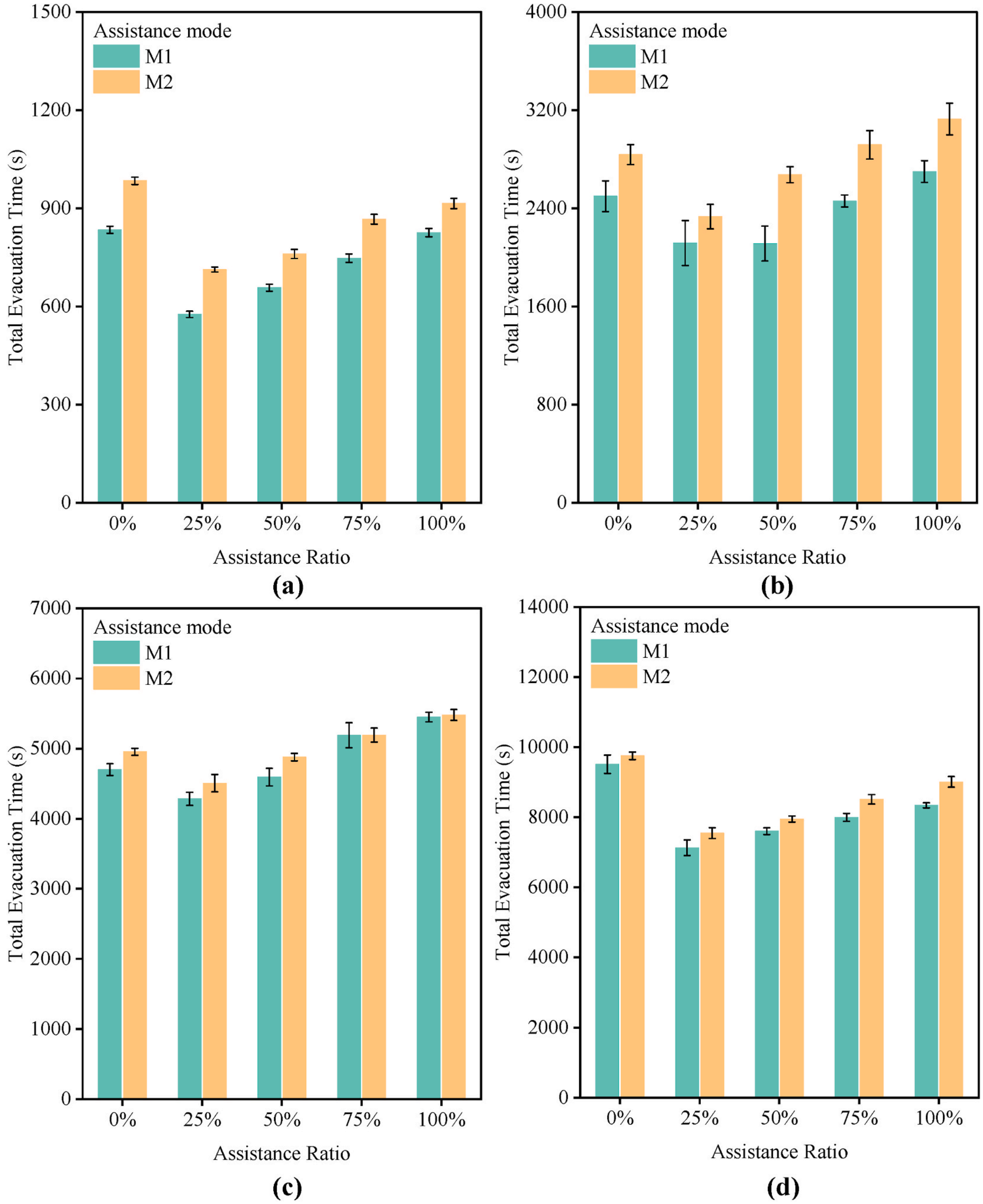

Fig. 10. TET results among different assistance modes when elevators are unavailable in (a) 8 stories, (b) 16 stories, (c) 24 stories and (d) 32 stories.

3.4. Analysis of evacuation equity

The preceding analyses in Sections 3.2 and 3.3 focused on TET as the primary metric for evaluating the overall efficiency of different assistance strategies. However, a comprehensive assessment of evacuation performance must extend beyond aggregate efficiency to consider the principle of evacuation equity, ensuring that vulnerable populations are not disproportionately affected. This is because even the low TET can mask significant underlying disparities, where the most vulnerable individuals are left behind or face dangerously long evacuation times, causing a critical issue in disaster ethics and planning [59].

Therefore, this section directly addresses this concern by disaggregating the results to analyze the time of last evacuee per group across 15 stochastic simulations for each distinct occupant group: wheelchair users, elderly, pediatric, adult female and male patients. By comparing the worst with the optimal assistance strategies summarized in Table 9, this analysis aims to identify the most vulnerable groups and quantify the crucial role of assistance in mitigating these vulnerabilities and promoting a fairer evacuation outcome. The

Table 9
Optimal assistance strategies for each working condition.

Working conditions	Assistance strategies	Total evacuation time/s
C1-1	M2-50 %	536.5 ± 6.6
C1-2	M1-40 %	560.8 ± 10.4
C2-1	M2-50 %	1809 ± 65.87
C2-2	M1-40 %	1962 ± 83.4
C3-1	M2-50 %	3678 ± 149.57
C3-2	M1-40 %	4177 ± 126.1
C4-1	M2-50 %	6502 ± 223.7
C4-2	M1-40 %	6954 ± 204.5

results are shown in Fig. 11 below.

Critically, the optimal assistance strategy achieved significant decrease in last evacuee evacuation time across all building heights. For instance, wheelchair users in 32 stories buildings evacuated in 13,220s under worst-assistance scenarios, but required only 6,500s on average with optimal assistance, cutting around half of the evacuation time. This universal efficacy demonstrates the robustness of our assistance framework in eliminating extreme delays. Also, the results consistently reflected the predefined mobility hierarchy, with

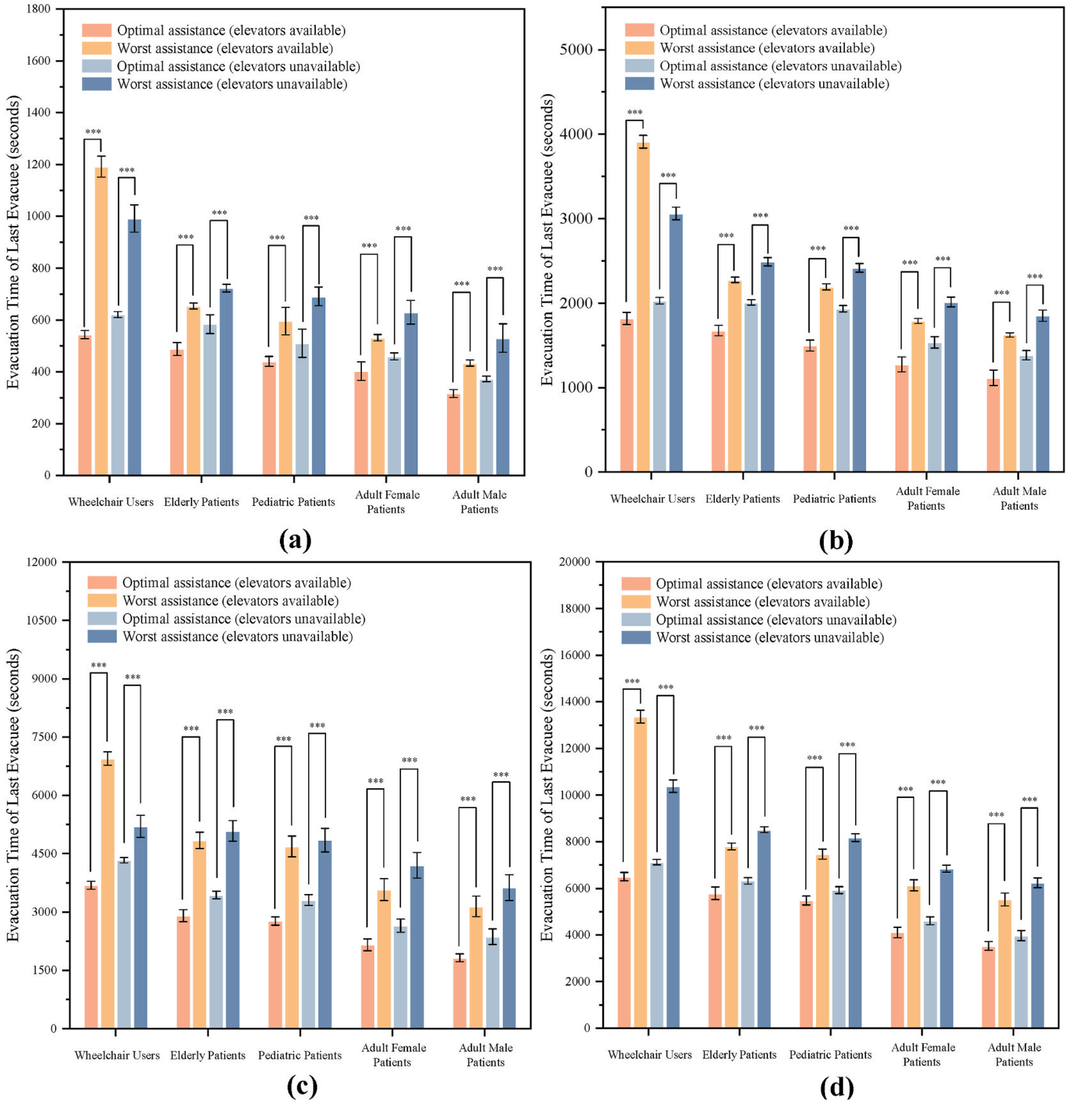

Fig. 11. Evacuation time of last evacuee among optimal and worst assistance strategies in (a) 8 stories, (b) 16 stories, (c) 24 stories and (d) 32 stories.

wheelchair users evacuating last, followed by elderly, pediatric, adult female, and adult male patients. This order directly corresponds to the movement speeds established in Table 5. Moreover, under worst-assistance scenarios, wheelchair users exhibited prolonged evacuation times when elevators are available compared to unavailable, a phenomenon unique to this group that aligns with the elevator congestion patterns documented in Fig. 7 (a). And all other occupant groups experienced reduced evacuation times with functional elevators.

4. Conclusions

This study systematically evaluates the impact of assistance behavior on evacuation efficiency in high-rise inpatient buildings through agent-based simulations. The findings reveal that the optimal assistance ratio is context-dependent, with 50 % assistance yielding the shortest evacuation time when elevators are operational, while a 40 % ratio proves most effective in elevator-unavailable scenarios. Priority-based assistance (M2) significantly outperforms proximity-based strategies (M1) in high-rise buildings with functional elevators. Conversely, M1 demonstrates superior efficiency in elevator-unavailable conditions by minimizing stairwell congestion through localized assistance and avoiding unnecessary vertical movement. Building height emerges as a critical determinant, with evacuation time increasing exponentially in ultra-high-rise structures (24 and 32 stories), necessitating tailored strategies for different architectural configurations. Moreover, optimized assistance strategies can significantly reduce extreme delays for all vulnerable groups, measured by the time of last evacuee across all building heights, enhancing evacuation equity.

Crucially, the study highlights the potential of social community empowerment, leveraging visitors and caregivers as auxiliary evacuation resources, to mitigate healthcare personnel shortages and enhance disaster resilience. These insights underscore the necessity of dynamic, infrastructure-sensitive protocols that adapt assistance ratios, modes, and evacuation pathway utilization to real-time conditions. To translate these findings into actionable policies, hospitals should prioritize integrating social community mobilization into emergency preparedness frameworks. First, standardized training programs for public volunteers should include modules on mobility assistance techniques and evacuation route navigation, aligned with guidelines from the Code for Design of General Hospitals (GB 51039-2014). Second, building code revisions should emphasize dual evacuation pathways to ensure accessibility for diverse mobility groups, particularly in multi-story facilities. Third, for high-rise hospitals, mandatory drills should test stairwell-based evacuation protocols under simulated elevator failure conditions. Urban planning policies should prioritize evacuation feasibility in hospital construction approvals for disaster-prone areas. Finally, collaborative platforms between healthcare institutions and technology providers should be established to develop adaptive evacuation solutions, ultimately fostering a resilient hospital system capable of safeguarding vulnerable populations during crises.

Although this study provides valuable insights into optimizing assistance strategies for hospital evacuations, there are still several limitations. Firstly, the simulations simplify human behavior by omitting pre-existing social relationships (e.g., kinship) and psychological factors such as panic propagation or herd mentality, which could influence decision-making and crowd dynamics in real-world scenarios. Secondly, the model assumes immediate evacuation initiation and excludes preparatory phases (e.g., reaction time, patient transfer to wheelchairs), potentially overestimating evacuation efficiency. Finally, while agent-based simulations provide robust theoretical insights, this study lacks of the empirical validation through real-world evacuation data. Future research should incorporate dynamic hazard progression, behavioral variability, and multi-institutional validation to refine these strategies.

CRediT authorship contribution statement

Jingjie Wang: Writing – original draft, Software, Data curation. **Yitian Luo:** Writing – original draft, Methodology. **Xiao Zhou:** Investigation. **Wenxuan Zhao:** Data curation. **Yang Lei:** Software. **Wei Xie:** Supervision, Funding acquisition, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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