

Article

Modeling Drone-Assisted Subway Fire Evacuation Based on Digital Twin and Human–Fire-Station Interaction

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Abstract

Subway fire evacuations face severe challenges due to high passenger density, spatial unfamiliarity, and toxic smoke, which often render traditional static signage ineffective and cause chaotic congestion. To address this, we propose a drone-assisted evacuation strategy evaluated via a high-fidelity digital twin platform coupling PyroSim and AnyLogic. The developed human–fire-station interaction model integrates CO-induced physiological degradation and a binary logit model to capture bounded-rational decision-making and herding behaviors. Using the Suzhou Olympic Sports Centre Station as a case study, simulations reveal that spatial familiarity’s impact on spontaneous evacuation exhibits strict diminishing marginal returns. Under a realistic low-familiarity scenario (25%), unguided evacuation requires 312 s with severe bottlenecking. Drone guidance actively intercepts this chaos, slashing clearance time to 237 s—a 24.0% improvement in efficiency. Furthermore, aerial directives successfully transform panicked clusters into structured platoons, mitigating stampede risks and ensuring the safe egress of vulnerable demographics. This study provides robust quantitative evidence for integrating unmanned aerial systems into smart transit emergency management, serving as a high-fidelity virtual testbed for future evacuation drills.

Keywords: subway fire evacuation; drone-assisted guidance; digital twin; human–fire-station interaction; bounded rationality; crowd dynamics



Academic Editors: Fabio D’Andreagiovanni and Mahmut Reyhanoglu

Received: 21 May 2026

Revised: 12 June 2026

Accepted: 6 July 2026

Published: 13 July 2026

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1. Introduction

As urban modernization accelerates, public transportation has become increasingly vital to urban transit networks. Subway systems, characterized by their high capacity, rapid transit speeds, and environmental efficiency, serve as the backbone of urban mobility. However, their unique structural attributes—such as enclosed subterranean spaces, high passenger density, and complex electrical infrastructure—pose severe challenges during emergencies, particularly fire outbreaks. The high potential for casualties and property damage within these restricted environments urgently necessitates the development of highly resilient and adaptive evacuation strategies.

Evacuating subway systems is inherently complex, as the success of an emergency egress heavily depends on crowd dynamics, exit accessibility, and bounded-rational individual decision-making under stress. While regular commuters may possess a baseline

understanding of the station layout, the unpredictability of a fire emergency rapidly disrupts established navigation strategies. More critically, current subway emergency protocols predominantly rely on static signage and ground-level human staff (e.g., duty officers). In severely congested environments, this reliance exposes a critical vulnerability defined as “human-guidance occlusion.” Under such conditions, auditory and visual instructions from ground-level personnel are completely blocked by the dense crowd, leading to cognitive overload, blind pathfinding, and fatal delays. To overcome these physical limitations, this study proposes an active drone-assisted guidance system. By leveraging unobstructed aerial mobility, drones serve as dynamic routing references, broadcasting clear directives from above to bypass line-of-sight limitations and actively restructure panicked crowds toward optimal routes.

To rigorously evaluate this active aerial intervention, the simulation platform must be capable of depicting the highly complex spatial topology of a subway station, reflecting severe crowding dynamics, and allowing for continuous trajectory adjustments. However, existing commercial evacuation tools (e.g., Pathfinder and MassMotion) excel primarily at pedestrian dynamics within idealized, regular building spaces. Their highly encapsulated architectures and closed interfaces pose immense challenges for deep, real-time multi-physics coupling, and they inherently lack the capacity to natively embed autonomous flying agents. To break these encapsulation bottlenecks, we developed a custom Agent-Based Modeling (ABM) framework, using the Suzhou Olympic Sports Centre Station—a critical high-traffic interchange hub—as a case study.

Methodologically, this study shifts the paradigm from isolated numerical simulations in idealized spaces to a deep, heterogeneous “Human–Fire–Station” interaction. By discretizing the complex subway topology into a virtual cell array, the research establishes a continuous and localized dynamic coupling. Environmental data, such as toxic smoke dispersion (Carbon Monoxide (CO) concentration) and temperature distribution generated by the Fire Dynamics Simulator (FDS), are processed via Python (3.9.12) and seamlessly integrated into AnyLogic using the Pypeline library [1]. This architecture enables a fine-grained feedback loop among the spreading hazard, localized pedestrian physiological degradation, and active drone trajectory algorithms, effectively bridging a critical methodological gap in complex underground applications [2–4].

In summary, this study explicitly addresses the fundamental deficiencies in current subway fire evacuation models and drone guidance strategies, offering three primary academic contributions:

1. This study pioneers active drone intervention to resolve the physical limitations of static signage and ground-level staff. Utilizing unobstructed aerial mobility, drones act as dynamic routing references that bypass line-of-sight occlusion, effectively preventing evacuees from resorting to blind pathfinding during severe crowd bottlenecks.
2. Overcoming the architectural constraints of commercial software, this study develops a custom, multi-layered ABM platform. By integrating FDS and AnyLogic via a Virtual Cell Array, it captures the fine-grained, dynamic interplay among toxic smoke dispersion, physiological degradation, and autonomous drone routing within a highly complex transit hub.
3. Addressing a critical gap in emergency behavioral mechanics, this research introduces a Logit-based discrete choice model calibrated with empirical passenger survey data. This quantitatively defines the probability of evacuees following aerial directives, grounding simulated human–machine interactions in robust mathematical and sociological evidence rather than idealized assumptions.

2. Related Work

2.1. Pedestrian Flow Simulation and Digital Twins Under Evacuation Conditions

Pedestrian flow simulations primarily fall into two categories: macroscopic models based on fluid dynamics and microscopic models focusing on individual behavior. Macroscopic models treat the crowd as a continuous medium, utilizing fluid dynamics [5] to describe the spatial and temporal distribution of parameters like density and velocity. For instance, Helbing et al. [6] used a macroscopic hydrodynamic model to illustrate sudden density fluctuations during a panic attack. Recently, fluid dynamics has been increasingly integrated with alternative approaches. Yuan et al. [7] combined event tree analysis, computational fluid dynamics, and evacuation modeling to simulate the spread of dangerous gases and subsequent pedestrian evacuation. Similarly, to identify optimal evacuation routes during poisonous gas leaks, Seo et al. [8] integrated deep neural networks within an integer programming optimization framework.

Conversely, microscopic models excel at capturing individual interaction details and heterogeneity, depicting human movement more accurately and naturally. Currently, the dominant micro-models include Cellular Automata (CA), ABMs, and the Social Force Model (SFM). Among these, the CA model [9] is highly appropriate for simulating complex systems due to its discrete spatiotemporal features and regional rule designs. For example, Varas et al. [10] enhanced Dijkstra's algorithm within a CA framework to optimize exit utilization, while Zheng et al. [11] built a dynamic smoke field by incorporating a fire spread model.

ABMs offer a highly flexible paradigm, utilizing both discrete and continuous spatiotemporal representations. They have evolved from rudimentary environment-aware modeling to the integration of multi-source data. Heliövaara et al. [12] developed a repulsive force model to analyze physical barrier avoidance, whereas D'Orazio et al. [13] formulated a group center-of-mass attraction model to coordinate group movements. Recent ABM research has also incorporated intricate elements like dynamic information dissemination; for instance, Harris et al. [14] simulated behavioral responses to emergency directives via external communication systems.

Furthermore, the SFM utilizes Newtonian mechanics to quantify the forces of attraction and repulsion between individuals [15]. Kirchner and Schadschneider [16] pioneered the use of the SFM to explain the micro-mechanisms of egress blockage. The SFM has since been refined for dense crowd scenarios: Yuen and Lee [17] proposed an overtaking mechanism to improve same-direction flow modeling, and Langston et al. [18] applied a three-circle representation to simulate pedestrian rotation in high-density contexts. To identify optimal paths dynamically, Berseth et al. [19] utilized a hybrid SFM approach with real-time feedback.

Despite the maturity of these individual models (e.g., SFM and ABM), modeling fire evacuations in complex transit hubs still faces certain methodological challenges, particularly in multi-physics coupling. Based on existing literature, these challenges can be primarily classified into two dimensions:

First, regarding environmental modeling and data coupling, a substantial body of research tends to simplify fire hazards as static obstacles, which may not fully capture their dynamic spatiotemporal propagation [20–22]. Furthermore, when multi-platform simulations are utilized to depict complex topologies—such as subway stations, underground mines, and university buildings—they often experience data decoupling. This separation makes it challenging to establish a continuous feedback mechanism between evolving fire dynamics and individualized agent behavior [23,24].

Second, concerning behavioral logic and environmental feedback, many contemporary models encounter difficulties in directly integrating physiological stress factors—such

as toxic exposure—into microscopic movement rules [25,26]. Consequently, routing algorithms primarily rely on predefined static parameters, which limit their adaptability to real-time environmental changes [2,27,28]. This structural constraint can lead to repetitive path-searching behaviors [29], difficulties in adapting to multi-hazard interactions [30], or degraded routing efficiency under extreme high-density bottlenecks [31]. Additionally, models heavily calibrated with specific empirical settings or simplified infrastructural assumptions may omit the dynamic constraints between crowd flow and physical facilities [32,33].

To address these unresolved issues, our study introduces a virtual cell array framework designed to bridge the data decoupling gap between macroscopic fire simulations and microscopic evacuation behaviors. Rather than applying uniform environmental penalties across broad areas, this framework discretizes the physical space into interconnected virtual cells. Each cell serves as an independent dynamic variable carrier, encapsulating real-time attributes (e.g., CO concentration, pedestrian density, facility status). By rigorously mapping FDS output data to these localized cells, the framework enables a genuine Human–Fire–Station interaction. As agents enter a specific cell, the local environmental attributes dynamically trigger individualized physiological and behavioral updates (e.g., modifying walking speed based on CO thresholds and updating path-choice logic). Ultimately, this cellular-based mapping mechanism achieves a data-driven, continuous closed loop, effectively overcoming the limitations of static environmental assumptions and providing a highly fine-grained foundation for evaluating dynamic drone-assisted interventions.

2.2. Modeling Agent Interaction for Evacuation Scenarios

Physiological factors play a fundamental role in determining evacuation capabilities. For example, Li et al. [34] categorized pedestrians into discrete speed groups (male, female, child, and elderly) while considering shoulder width. Although this method increases computing efficiency, individual differences are not fully captured by deterministic values. Advancing this, the dynamic grouping model by Barnes et al. [35] utilized a continuous age function to assign speeds, detailing physiological distinctions more comprehensively. Building upon these foundations, our study introduces stochastic speed variance (e.g., normal distributions calibrated by age and gender) to accurately reflect unobserved demographic heterogeneity. More importantly, this physiological baseline is dynamically coupled with localized hazard exposure, allowing agent movement capabilities to realistically degrade under environmental stress.

Psychological variables critically influence individual decision-making during evacuations. Research indicates a strong tendency for individuals to select familiar routes over strictly shortest paths, which often leads to severe spatial bottlenecks. Furthermore, stress and panic levels have been quantified across various models. Yang et al. [36] measured psychological stress by evaluating personality traits that influence panic and impatience, while Wang et al. [37] proposed that panic is driven by proximity to the hazard source and perceived crowd density. Moreover, Cao et al. [38] evaluated psychological stress using a sinusoidal function related to fire source proximity, demonstrating that when panic exceeds a certain threshold, it triggers congruent herd behaviors, exacerbating crowding. However, existing literature rarely addresses how such psychological stress influences the acceptance of active, external routing interventions. To bridge this gap, our study extends beyond traditional panic-induced herding by introducing a Logit-based discrete choice model. This mathematically quantifies human–drone compliance, capturing the nuanced behavioral mechanics of evacuees as they process dynamic aerial guidance under severe stress.

At the environmental level, individual conduct is heavily governed by spatial perception and localized hazard evolution [39,40]. Fire spread and its derivatives are the most critical external variables. Benseghir et al. [41] quantified real-time fire impacts using FDS, reducing prediction errors from $\pm 15\%$ to $\pm 7\%$. Similarly, Liu et al. [42] converted derivatives like CO concentration and temperature into pedestrian path costs. Chen et al. [43] investigated the chain reaction of temperature and visibility in ship fires, noting an exponential deterioration in navigation efficiency when visibility drops below three meters. Additionally, infrastructure deterioration heavily impacts exit availability [44–46]. Zhang et al. [47] addressed this via a dynamic path planning method using navigation grids, improving evacuation efficiency by 12.53%. Despite these advancements, tightly coupling continuous fire data with discrete agent behavior remains a challenge. Our research resolves this by mapping real-time FDS outputs into a Virtual Cell Array, enabling a high-fidelity Human–Fire–Station interaction where localized environmental degradation and dynamic facility constraints directly update agent path-choice logic.

In summary, effective evacuation modeling requires a seamless integration of physiological, psychological, and environmental dimensions. At the physiological level, this study incorporates demographic attributes with stochastic variance to model realistic capability profiles. At the psychological level, we expand beyond basic spatial familiarity and herding to mathematically quantify dynamic human–machine interactions via a targeted Logit framework. At the environmental level, the implementation of a cellular-based mapping mechanism synthesizes real-time CO concentrations, facility statuses, and crowd density. This tri-level integration transcends conventional decoupled simulations, ensuring a highly accurate, data-driven replication of the complex heterogeneous dynamics inherent in drone-assisted subway evacuations.

2.3. Evacuation Guidance Strategy and Drone Application

Evacuation guidance strategies are broadly classified into traditional, intelligent, and drone-assisted approaches. Traditional strategies predominantly rely on manual ground-level guidance or static signage, which struggle to adapt to real-time hazard propagation. For example, Abdelghany et al. [48] provided optimal exit information via simulation-optimized static designs, and Filippidis et al. [49] developed an Active Dynamic Signage System using flashing LEDs. However, these conventional methods are constrained by fixed assignment procedures and line-of-sight limitations. In severely congested environments, they frequently suffer from “human-guidance occlusion,” where dense crowds block auditory and visual instructions from ground staff, ultimately leading to cognitive overload and blind pathfinding.

With the advancement of information technology, intelligent computational models have increasingly optimized evacuation decision-making. Li et al. [50] combined real-time fire propagation prediction with BIM-based spatial modeling to enable dynamic path adjustments. Reinforcement learning (RL) has also been proposed for adaptive guidance under limited visibility. Xue et al. [51] established a guidance method based on a combined action-space DQN algorithm to manage complex inter-crowd interactions, while Dong et al. [52] integrated real-time environmental data (e.g., fire spread, smoke, crowd density) with an improved A* algorithm and RL. Furthermore, virtual reality (VR) has catalyzed significant advancements in training paradigms: Gu et al. [53] proposed a metaverse-based training system using deep RL, and Zhang et al. [54] utilized VR to simulate competitive guidance under time constraints. While these intelligent optimization approaches have significantly improved routing algorithms, they are often confined to idealized simulations and lack integration with active physical interventions.

Recently, small unmanned aerial vehicles (UAVs or drones) have emerged as highly promising tools for active emergency intervention, leveraging their unobstructed aerial mobility. Cooperative multi-drone systems have been developed, where main drones (equipped with cameras for hazard identification) deploy smaller agents to guide individuals lacking communication devices [55]. Deep reinforcement learning coupled with dynamic path planning has further enhanced autonomous drone decision-making [56]. Moreover, research indicates that drones can rapidly adjust routes using stochastic optimal intervention techniques and chaos theory to manage macroscopic crowd movements [57].

Despite these promising technological advancements, existing drone-assisted evacuation studies frequently rely on idealized spatial layouts and often treat drones merely as passive observation or mapping tools. Crucially, they tend to omit the microscopic behavioral mechanics of how panicked crowds perceive and comply with aerial guidance under stress. To bridge these methodological gaps, this study proposes an active drone guidance strategy specifically designed to overcome “human-guidance occlusion” in high-density transit hubs. By establishing a comprehensive virtual cell array framework, we develop a custom digital twin that achieves a genuine, fine-grained Human–Fire–Station interaction. This architecture rigorously couples real-time environmental hazards (dynamic CO diffusion via the AnyLogic-Pypeline API) with dynamic drone routing based on real-time density metrics. Furthermore, rather than assuming idealized pedestrian compliance, we integrate a targeted Logit-based discrete choice model to mathematically quantify the human–machine interaction, rigorously evaluating the complex impact of spatial familiarity and dynamic herding behaviors on overall evacuation efficiency.

3. Concepts of Human–Fire–Drone Guidance Evacuation Model

3.1. Drone Guidance Strategy in a Fire Scenario

To achieve intelligent management within subway stations, unmanned aerial vehicles (UAVs, hereafter referred to as drones) are typically stationed at dedicated bases capable of automated charging. As illustrated in Figure 1, these drones are equipped with essential payload modules, including high-definition cameras, directional acoustic hailers, and lightweight visual displays. By connecting to the station’s centralized monitoring system via a local area network, they facilitate the real-time monitoring of passenger flows, hazard detection, and the continuous updating of the station’s digital twin. During peak operational hours, when severe congestion prevents on-duty staff from accessing critical areas promptly, drones can be rapidly deployed to alleviate bottlenecks and broadcast navigational directives. The synergy between autonomous drone operations and human management personnel enables the execution of complex crowd-control measures, thereby elevating the intelligence and responsiveness of the station’s emergency protocols. While this study focuses on subway environments, such drone-based pedestrian flow management possesses broad applicability across other high-capacity transit hubs, such as high-speed railway stations and large commercial complexes.

In the event of a fire, degraded spatial awareness and panic-induced herd behavior frequently compel pedestrians toward suboptimal or hazardous exits, severely exacerbating congestion and evacuation delays. Under intense psychological stress, even passengers with high spatial familiarity may irrationally default to habitual but obstructed paths. To mitigate these cognitive lapses, dynamic and highly visible guidance strategies are paramount. Traditional, human-centric leader-based protocols are fundamentally constrained by the leader’s grounded position and limited communicative reach in a chaotic, noisy environment. To overcome this, this study introduces drones as “aerial leaders.” Operating at optimal altitudes above the crowd, drones bypass physical floor-level obstacles to deliver clear, wide-range audiovisual guidance.

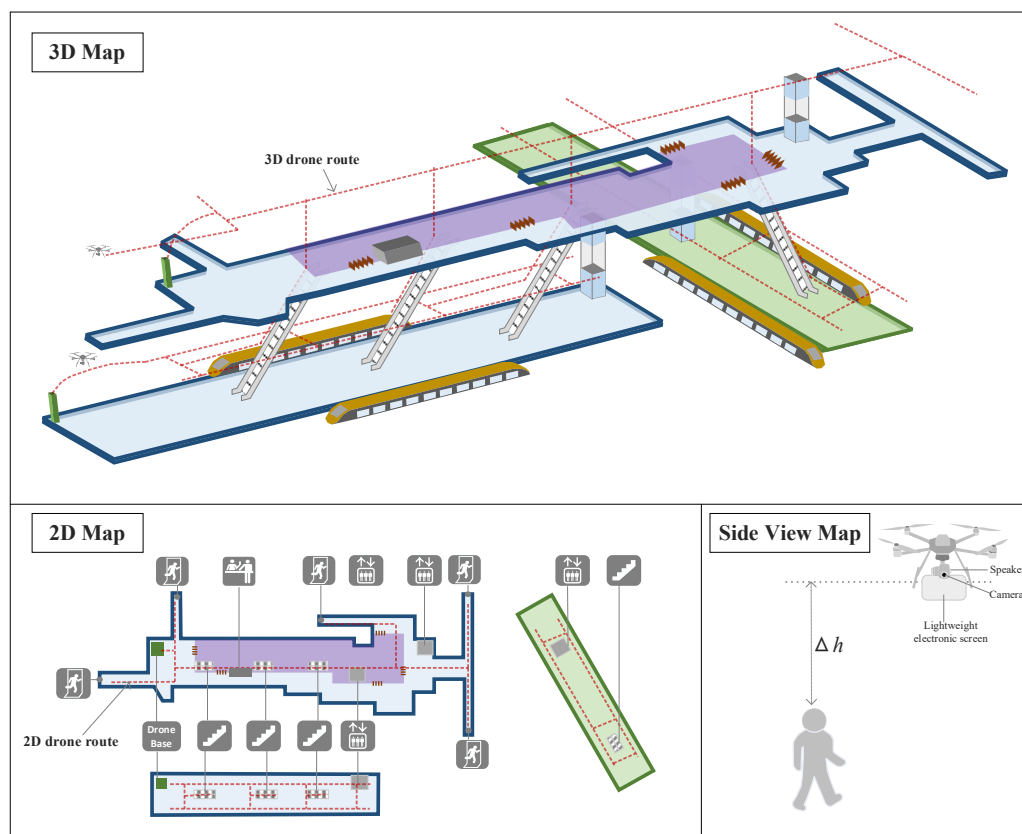


Figure 1. The details of the drone guide for stations.

To mathematically define the drone's dynamic deployment, the station is discretized into a set of predefined spatial grid cells, denoted as I . At any given time step t , the drone continuously evaluates the criticality of each cell $i \in I$ to determine its optimal target destination ($\text{Cell}_{\text{target}}^*$). This decision is governed by an objective function that maximizes a weighted combination of real-time pedestrian density (ρ_i^t) and CO concentration (C_i^t):

$$\text{Cell}_{\text{target}}^* = \underset{i \in I}{\operatorname{argmax}} \left(\omega_1 \frac{\rho_i^t}{\rho_{\max}} + \omega_2 \frac{C_i^t}{C_{\max}} \right) \quad (1)$$

where $\rho_{\max}$ and $C_{\max}$ are the maximum observed density and CO concentration used for normalization, respectively. The weighting coefficients, ω_1 and ω_2 (where $\omega_1 + \omega_2 = 1$), represent the relative priority assigned to congestion relief versus hazard avoidance. Once $\text{Cell}_{\text{target}}^*$ is identified, the drone utilizes shortest-path algorithms within the obstacle-free aerial space to navigate to the high-risk cluster and initiate its guidance protocol.

Upon reaching the target zone, pedestrians make independent, bounded-rational decisions regarding whether to comply with the drone's directives. The physical movement of these followers remains heterogeneous, constrained by individual demographic factors such as age, gender, and physical stature. As depicted in Figure 2, under the drone's sustained guidance, the initially disordered and panicked crowd gradually self-organizes into a structured, cohesive platoon. Furthermore, this dynamic process frequently facilitates the natural emergence of a "secondary human leader" at the front of the pedestrian queue, who effectively relays and reinforces the drone's guidance to nearby individuals within their immediate local radius.

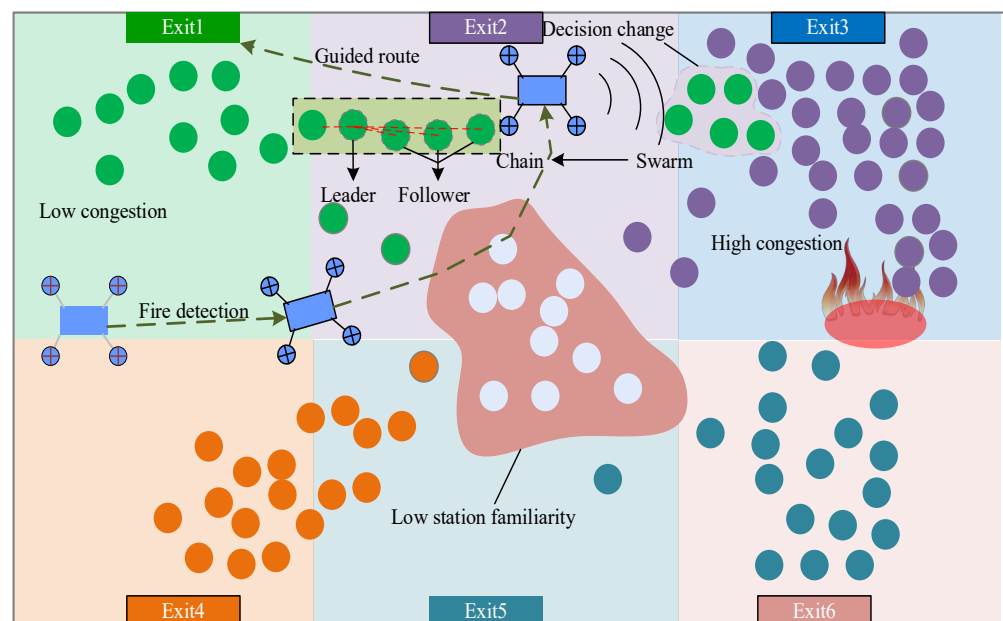


Figure 2. Conceptual description of the drone guidance strategy.

3.2. Human–Fire–Station Interaction Model

This study models pedestrian movement dynamics within the station using SFM as the foundational framework. The SFM mathematically captures the interplay of self-driven motivations, interpersonal repulsions, and obstacle-to-person forces. Specifically, an individual's trajectory is continuously adjusted by an attractive force toward a destination (e.g., an evacuation exit) alongside repulsive forces exerted by neighboring pedestrians and physical barriers, ensuring collision avoidance and goal-oriented navigation.

To accurately capture the unobserved heterogeneity and natural variance in human locomotion, initial pedestrian walking speeds are modeled as stochastic variables rather than deterministic constants. Specifically, the initial speed [58,59], V , is assigned following a truncated normal distribution, $V \sim N(\mu, \sigma^2)$, parameterized by age (categorized into children, youth, middle-aged, and elderly) and gender. Table 1 details the mean (μ) and standard deviation (σ) of the initial speed distributions for these varying demographic groups. The truncation ensures that realistic biomechanical boundaries (e.g., absolute minimum speeds) are strictly maintained during the simulation initialization.

Table 1. Initial walking speed distribution across demographic groups.

Demographic Group	Male Speed (m/s) ($\mu \pm \sigma$)	Female Speed (m/s) ($\mu \pm \sigma$)	Parameter Notation
Children	0.95 ± 0.15	0.90 ± 0.15	V_c
Youth	1.35 ± 0.22	1.25 ± 0.20	V_y
Middle-aged	1.25 ± 0.20	1.15 ± 0.18	V_m
Elderly	0.95 ± 0.16	0.85 ± 0.15	V_e

The propagation of fire-induced hot smoke—characterized by low density and buoyancy-driven ceiling jets—is modeled using Large Eddy Simulation (LES) within a computational fluid dynamics framework. As smoke propagates through the subway station's complex topology, adjusting its path upon encountering obstacles, toxic gases and particulate matter disperse beyond the immediate fire zone. CO concentration serves as a critical proxy for hazard assessment in this enclosed environment. While ambient CO lev-

els typically hover between 0.1 and 0.2 ppm, the accumulation of CO in flue gases severely impairs pedestrian physiological functions. Notably, when CO concentrations exceed a critical threshold of 1600 ppm, evacuation speeds degrade significantly [42,60]. Rather than employing a rigid linear drop, the physiological degradation of movement capability is captured via a continuous exponential decay function, ensuring both mathematical smoothness and physiological realism, as described in Equation (2):

$$V' = V_t + (V - V_t) \cdot \exp(-\gamma \cdot \max(0, P_{co} - P_c)) \quad (2)$$

where V' denotes the updated walking speed of specific age and gender groups under the influence of varying CO concentrations (P_{co}). The initial speed, V , is dynamically drawn from the stochastic distributions detailed in Table 1, with female mean speeds intrinsically scaled by an approximate factor of 0.8 relative to their male counterparts. V_t represents the absolute minimum walking speed, constrained to 0.2 m/s. The critical CO threshold, P_c , is established at 1600 ppm. Crucially, γ represents the physiological decay rate induced by toxic exposure. This exponential formulation ensures that when P_{co} remains below P_c , the speed maintains its baseline V ; however, upon surpassing the threshold, the pedestrian's speed smoothly decelerates, asymptotically approaching the minimum mobility threshold V_t under extreme hazard conditions.

During a fire emergency, the spatiotemporal evolution of pedestrian evacuation is strictly governed by four primary constraints: (i) goal-directed navigation toward connecting passageways and concourse-level exits (incorporating ticketing and security zones); (ii) spatial compression resulting from high-density pedestrian flows, which restricts free movement and induces congestion; (iii) physical interactions with static infrastructural elements (e.g., structural columns, retaining walls, and handrails); and (iv) physiological degradation of movement capabilities due to varying spatial concentrations of CO. Synthesizing these behavioral, physical, and environmental dynamics, a comprehensive human–fire–station interaction framework is established, as illustrated in Figure 3.

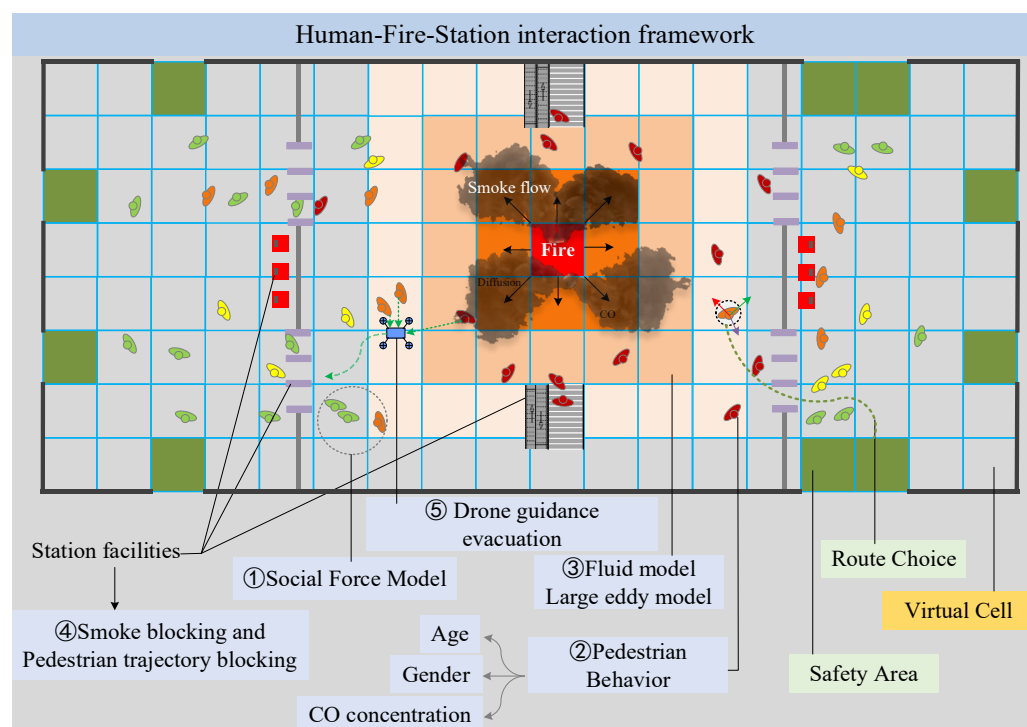


Figure 3. Conceptual description of human–fire–station model.

3.3. Pedestrian Following Behavior and Drone Choice Under Fire Evacuation

To precisely monitor environmental hazards, this study partitions the station into a grid of basic spatial cells, each conceptually equipped with detectors to gauge localized CO concentrations. Elevated CO levels not only signify heightened regional danger but also accelerate the physiological degradation of evacuees. Under such severe emergency constraints, panicked pedestrians are increasingly inclined to abandon their predefined or obstructed routes and follow the drone as an intuitive, high-visibility evacuation alternative.

In this proposed evacuation paradigm, the drone assumes a dynamic leadership role. However, given the bounded rationality of individuals and chaotic environmental stressors, absolute compliance with the drone's guidance is not guaranteed. Consequently, we formulate a binary logit model within a discrete choice framework to simulate the decision-making process of passengers. The choice set consists of two alternatives: "following the drone" or "maintaining the original route." The utility function governing this decision is expanded to account for not only environmental stimuli but also dynamic social conformity (the herding effect), as defined in Equation (3):

$$U_{\text{change}} = V_{\text{change}} + \varepsilon_{\text{change}} \\ = \text{ASC}_{\text{inertia}} + \beta_{\text{CG}} \left(\frac{\text{CONG}_n - \text{CONG}_{\text{min}}}{\text{CONG}_n} \right) + \beta_{\text{CO}} \cdot P_{\text{co}} + \beta_d \cdot \text{DIS} + \beta_a \cdot \text{Age} + \beta_h \cdot \text{HERD} \quad (3)$$

where U_{change} is the perceived utility of changing decisions to follow the drone, V_{change} represents the observable systematic utility component, and $\varepsilon_{\text{change}}$ denotes the unobserved error term capturing individual behavioral randomness. The systematic utility comprises five explanatory variables and an Alternative-Specific Constant ($\text{ASC}_{\text{inertia}}$).

The first variable captures exit congestion, normalized to reflect relative crowding: CONG_n is the pedestrian density at the originally chosen exit n , and CONG_{min} is the density at the least congested available exit. A higher ratio indicates severe crowding at the current target, strongly incentivizing the pedestrian to accept drone guidance. P_{co} represents the localized CO concentration, and DIS defines the dynamic spatial distance from the pedestrian to their currently chosen exit n , which is continuously updated based on evolving congestion distributions.

Furthermore, individual heterogeneity is integrated via the Age variable, coded as a binary indicator. Recognizing the heightened vulnerability and diminished spatial cognitive capacities of certain demographics under stress, Age is set to 1 for children and the elderly, indicating a greater inherent reliance on external guidance. Conversely, youth and middle-aged pedestrians are assigned a value of 0. $\text{ASC}_{\text{inertia}}$ captures the psychological inertia associated with maintaining a pre-selected route; this constant crucially prevents the model from generating unrealistically high decision-switching frequencies, thereby stabilizing the simulation.

Crucially, the newly introduced variable, HERD, represents the localized herding effect. It is defined as the proportion of neighboring pedestrians within an individual's visual radius who have already chosen to follow the drone. The corresponding coefficient, β_h , quantifies psychological susceptibility to crowd conformity. This unified utility formulation effectively captures the cascade mechanism of evacuation decisions. Initially, when the fire breaks out ($\text{HERD} \approx 0$), the "first wave" of pedestrians makes independent decisions driven primarily by severe environmental stressors. As these early adopters begin moving behind the drone, the localized HERD value rapidly increases. This dynamic surge in peer-induced utility triggers a secondary wave of followers, accurately modeling the realistic phenomenon where panicked individuals instinctively mimic the escape actions of adjacent crowds.

The probability (P_{change}) that a passenger chooses to follow the drone is mathematically expressed by the standard logistic distribution in Equation (4):

$$P_{\text{change}} = \frac{1}{1 + e^{-V_{\text{change}}}} \quad (4)$$

Within this binary framework, an individual actively decides to follow the drone if $P_{\text{change}} \geq 0.5$; otherwise, they persist with their initial evacuation strategy. Notably, the elegant, closed-form structure of the logit model ensures high computational efficiency, a critical requirement when simulating massive crowd dynamics in a digital twin environment.

To empirically calibrate this model, 350 valid responses were extracted from a targeted “Passenger Evacuation Survey.” Standard logistic regression techniques [61,62] were subsequently applied to estimate the behavioral parameters (β) presented in Table 2.

Table 2. Calibrated parameter estimates for the binary logit decision model.

Parameter	Description	Estimated Value
$ASC_{inertia}$	Alternative-specific constant (decision inertia)	−7.50
β_{CG}	Coefficient for relative exit congestion	3.50
β_{CO}	Coefficient for CO concentration	1.75
β_d	Coefficient for dynamic distance to exit	1.75
β_a	Coefficient for demographic age indicator	0.80
β_h	Coefficient for localized herding effect	2.50

4. Simulation and Analysis

4.1. Investigation and Calibration

To rigorously validate the proposed evacuation model, the Suzhou Olympic Sports Centre Station is selected as the empirical case study. Unlike conventional transit hubs, this station serves as a critical three-level underground interchange (serving Lines 5 and 6) that faces extreme spatiotemporal passenger surges, particularly during large-scale stadium events (e.g., concerts and major sports matches). This unique operational context results in a highly heterogeneous passenger composition, blending regular daily commuters with a massive influx of event attendees who typically possess exceptionally low spatial familiarity with the station’s complex layout.

Extensive field investigations were conducted to calibrate the foundational parameters of the digital twin. The station encompasses seven primary exits, among which Exits 2, 4, and 5 directly service the main stadium and commercial plaza, thus bearing the heaviest egress pressure. Spatial constraints—including a 5 m ceiling height, 1 m wide escalators (operating at 0.5 m/s), and strategically distributed fare gates across all exits—were precisely mapped.

Real-world pedestrian flow dynamics were captured via peak-hour observational sampling (e.g., Saturday, 11:00–12:00). Data reveals a heavy asymmetric flow distribution: Exit 2 handles approximately 42.67% of the total outbound traffic, while Exit 4 accommodates 35.71% of inbound traffic. Furthermore, micro-behavioral parameters were calibrated based on empirical timing: average ticketing time is 65 s, security check requires 6 s, and fare gate passage takes 2 s (with 95.23% of passengers utilizing QR code scanning).

Train operational parameters, including a 6-car configuration, 360 s headway, and 35 s dwell time, were also integrated to ensure high-fidelity simulation initialization.

4.2. Digital-Twin Simulation Platform Configuration

To characterize the complex human–fire–station interaction, as shown in Figure 4, a high-fidelity integrated simulation platform was developed, sequentially coupling the FDS (PyroSim 2024.1) with AnyLogic (8.9.4) ABM. Central to this platform is the implementation of a virtual cell array, which discretizes both the physical subway environment and the unfolding fire field into independent computational units. Each cell functions as a dynamic variable carrier, seamlessly encapsulating localized environmental attributes—such as CO concentration, thermal gradients, and passenger density—alongside embedded behavioral methods, including local pathfinding and tiered speed modification rules. By binding these real-time properties to agent and facility states via rigorous coordinate transformations and script-parsed alignments, the cellular framework establishes a bidirectional, multi-physics closed loop where localized toxic diffusion directly degrades agent physiology and dynamically updates equipment-routing logic (e.g., ticket gates and escalators).

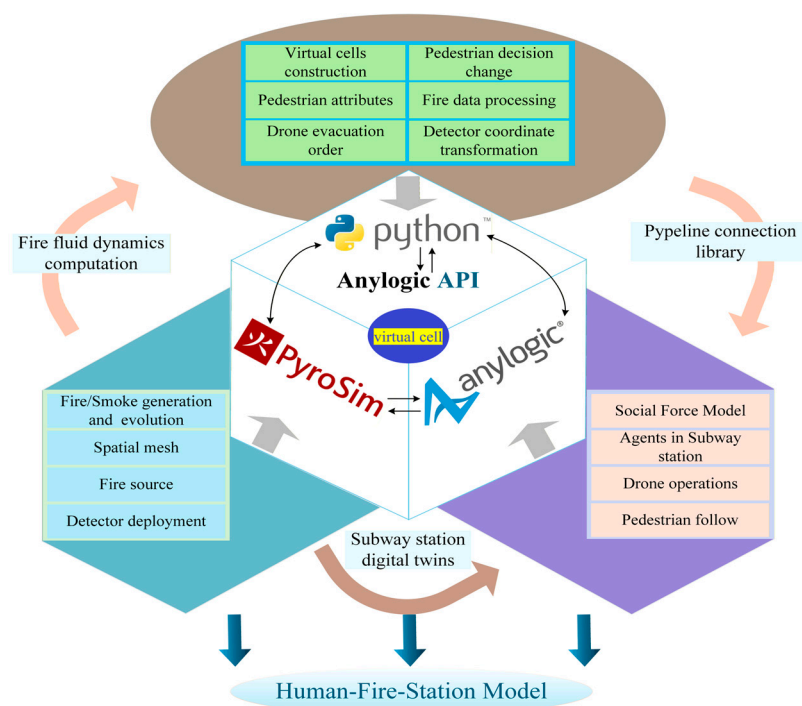


Figure 4. Framework of the integrated fire simulation–drone guidance evacuation digital-twins platform.

PyroSim is utilized to simulate fire thermodynamics and dynamic smoke propagation. The entire station is discretized into high-resolution spatial grid cells for fluid calculation. The optimal grid size is parameterized by the characteristic diameter of the fire source (D^*), which numerically defines the cutoff scale of the smallest influential eddy currents in the LES formulation. Due to the inherent non-linear dependencies derived from fluid dynamics, the resulting D^* value forms a complex multi-dimensional constraint space.

Figure 5 graphically depicts this non-linear sensitivity of the characteristic diameter (D^*) with respect to variations in the heat release rate (Q) and the ambient environmental temperature (T_0) within the subway station. The smooth non-linear surface illustrates a significant power-law relationship: D^* escalates rapidly as fire intensity scales towards fully developed megawatt ranges but gradually exhibits a decelerating growth rate. Si-

multaneously, temperature fluctuations introduce crucial non-linear variances to these scaling constraints.

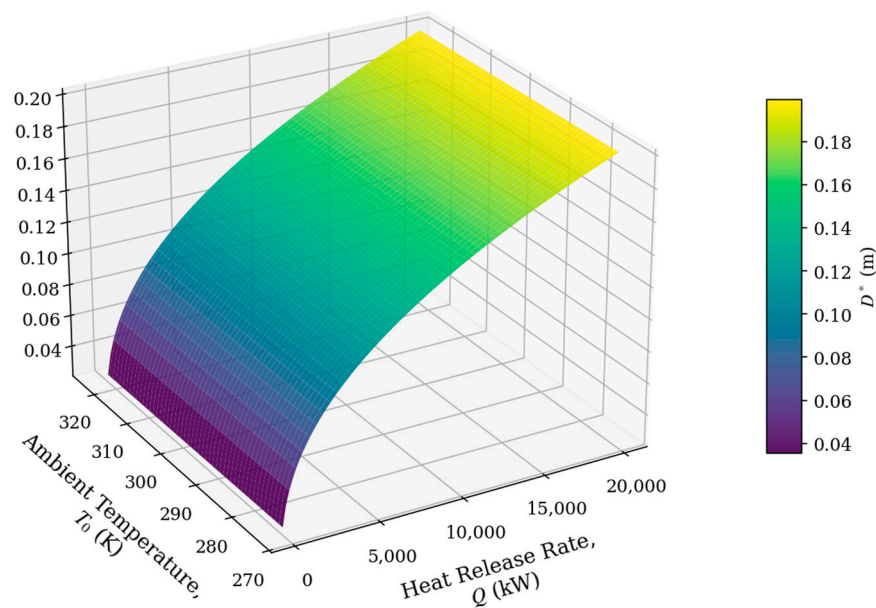


Figure 5. Non-linear sensitivity of the characteristic fire diameter (D^*) to heat release rate and ambient temperature.

This unique thermodynamic curvature provides the foundational justification for optimizing the finite-volume mesh resolution within PyroSim, ensuring that numerical sensitivity remains strictly bounded amidst varying hazard magnitudes and seasonal environmental conditions. Guided by this fluid dynamics constraint, the station's spatial grid is parameterized, and virtual CO concentration detectors are systematically deployed throughout the model at intervals of 3 m. These detectors are strategically positioned at a height of 1.6 m to perfectly align with the average respiratory elevation of the evacuating pedestrians. The weighting coefficients, ω_1 and ω_2 are 0.5. The parameters of the SFM in AnyLogic are calibrated by the study of Li et al. [63], and simulation is shown in Figure 6.

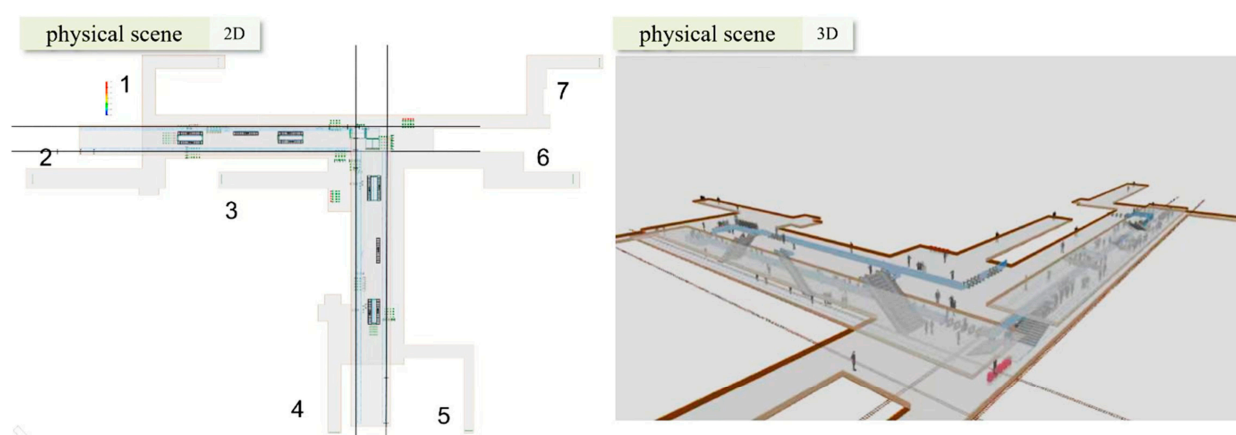


Figure 6. Detailed views of the Suzhou Olympic Sports Centre Station in AnyLogic.

4.3. Simulation and Discussion

4.3.1. Pedestrian Evacuation Analysis Under Different Familiarities

Before evaluating the drone intervention, the impact of spatial familiarity on spontaneous evacuation must be rigorously quantified. Figure 7a–c visually capture the microscopic spatiotemporal evolution of the unguided evacuation process, disaggregated

by four distinct demographic groups (children, youth, middle-aged, and elderly) under varying familiarity proportions (25%, 50%, and 75%). As observed in the subplots, the youth and middle-aged groups, possessing higher inherent walking speeds (as defined in Table 1), exhibit rapid initial decline rates. Conversely, the elderly's and children's curves invariably form a prolonged “evacuation tail.” Notably, in the extreme 25% familiarity scenario (Figure 7a), all demographic curves exhibit significantly extended plateaus, indicating severe spatial disorientation and chaotic bottlenecking caused by bounded rationality and herd mentality.

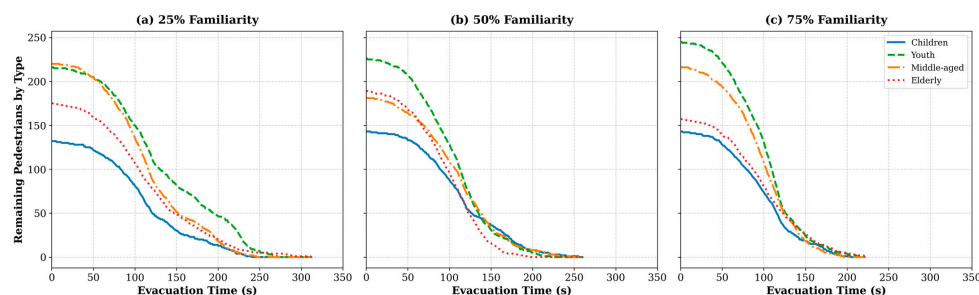


Figure 7. The spatiotemporal process of spontaneous evacuation by demographic types: (a) 25%, (b) 50%, (c) 75%.

To quantitatively assess the macro-level impact of these micro-behaviors, Figure 8 illustrates the aggregate efficiency curves for the three scenarios. As expected, a higher penetration rate of familiar pedestrians shortens the overall evacuation time cost. However, a deeper comparative analysis reveals a critical non-linear trend. When spatial familiarity increases from 25% to 50%, the overall evacuation time cost drops significantly from 312 s to 256 s—a substantial reduction of 17.9%. Yet, when familiarity further increases from 50% to 75%, the total time only decreases by 35 s (to 221 s), representing a diminished reduction rate of 13.7%.

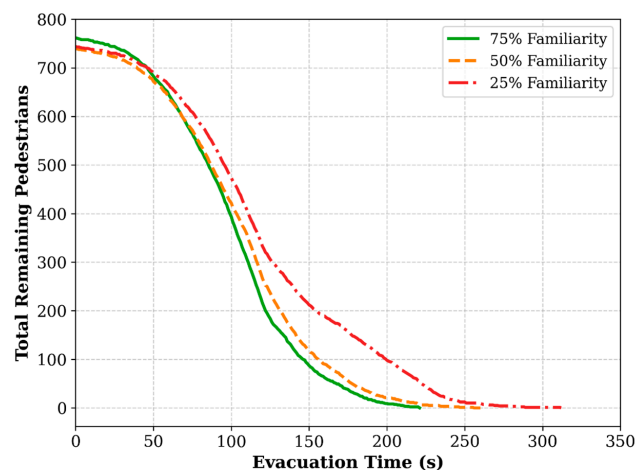


Figure 8. Evacuation efficiency analysis under different familiarities.

4.3.2. Comparative Analysis of the Drone Evacuation Strategy

To empirically validate the drone-assisted evacuation strategy, the 25% familiarity scenario—which most accurately reflects the challenging demographic reality of stadium event days—is selected as the primary baseline, while concurrently aligning with the empirical insights derived from our real-world passenger survey.

Figure 9a,b provide a critical microscopic comparison of the demographic egress dynamics with and without drone intervention. In the unguided scenario (Figure 9a), the

lack of clear directional information exacerbates the physiological disadvantages of vulnerable groups, resulting in a distinctly delayed clearance for the elderly and children. Conversely, under the dynamic aerial guidance (Figure 9b), the evacuation curves for all demographic groups compress significantly. Upon receiving the drone's visual and acoustic directives, the panicked evacuees rapidly transition from scattered, disordered clusters into organized, chained queues. This structured platooning mechanism actively clears pathways, enabling vulnerable pedestrians to sustain a steady egress pace while drastically mitigating the probability of crowd stampedes.

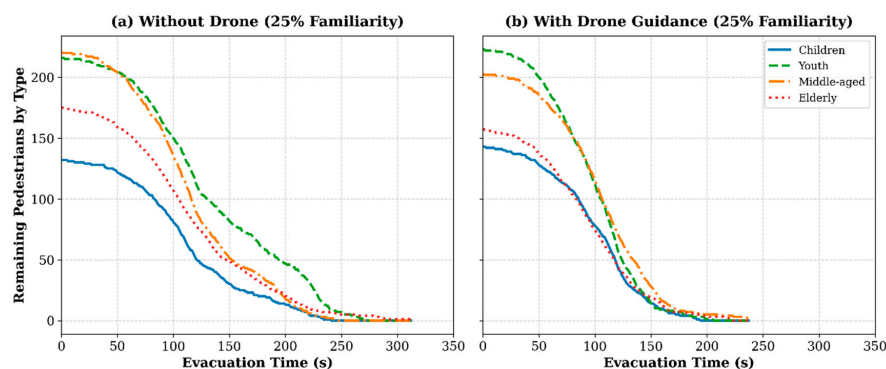


Figure 9. Comparative analysis of demographic evacuation processes. (a) Without Drone (25% Familiarity); (b) With Drone Guidance (25% Familiarity).

The macro-level efficiency leap brought by this micro-level behavioral optimization is vividly demonstrated in Figure 10. The introduction of aerial guidance triggers a dramatic improvement in performance. Under drone guidance, the total evacuation cost is slashed from 312 s to merely 237 s. This absolute reduction of 75 s equates to a remarkable 24.0% efficiency improvement. Crucially, the evacuation capacity achieved under this drone-guided 25% familiarity scenario (237 s) closely rivals the spontaneous evacuation of a highly familiar (75%) crowd (221 s). This quantitative evidence definitively proves that deploying an intelligent, adaptive external guidance system is a far more robust and impactful safety paradigm than relying on the unpredictable inherent spatial awareness of transit passengers.

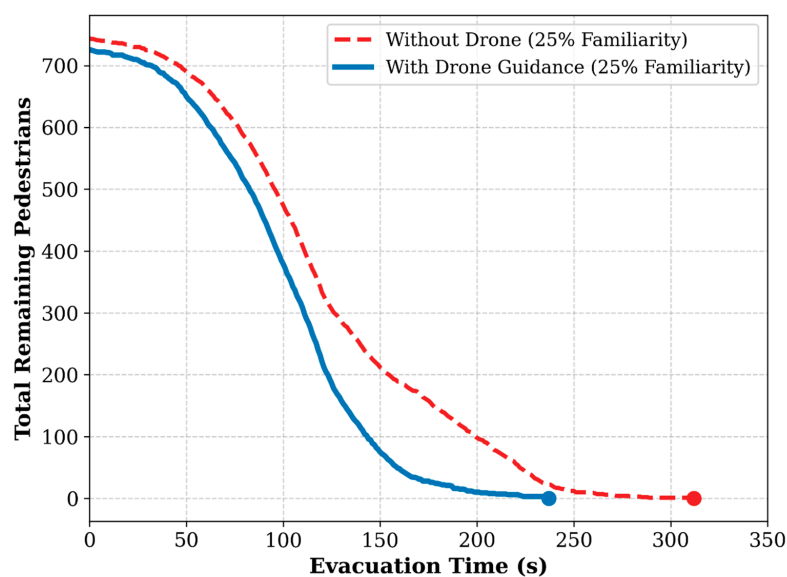


Figure 10. Efficiency analysis of drone guidance in the low-familiarity scenario (25% familiarity).

4.3.3. Evacuation Duration Analysis

Figure 11 presents the evaluation of evacuation durations across varying levels of spatial familiarity (0.25, 0.50, and 0.75), where no drone assistance is provided. The evaluation highlights the critical vulnerability of passengers within complex subway environments when they lack sufficient environmental knowledge. Under the lowest familiarity setting (0.25), evacuation durations spike dangerously across all groups, peaking at 312 s for the elderly and 272 s for the youth. As spatial familiarity increases to 0.75, the overall evacuation efficiency naturally improves, with middle-aged passengers clearing the station in 196 s and youth in 215 s. This trend emphasizes a fundamental deficiency in traditional evacuation relying solely on static signage: when passengers are unfamiliar with the subterranean layout, their decision-making under stress is severely impaired. This leads to erratic pathfinding, blind searching, and prolonged exposure to toxic smoke. Such empirical evidence firmly justifies the necessity for deploying dynamic, external routing interventions—such as the proposed drone system—to proactively compensate for the inherent spatial disorientation experienced by evacuees during sudden fire emergencies.



Figure 11. Evacuation Duration by Demographic Group (Without Drone Assistance).

Figure 12 illustrates the comparative evacuation durations of four distinct demographic groups under the most adverse spatial familiarity condition (familiarity = 0.25), contrasting scenarios with and without active drone assistance. The data demonstrates that the integration of drone guidance significantly enhances evacuation efficiency across all passenger categories. The most pronounced improvements are observed among highly vulnerable demographic groups. Specifically, the evacuation duration for the elderly population experiences a substantial reduction from 312 s to 223 s (an 89 s improvement), while the clearance time for children decreases from 241 s to 194 s. The youth demographic also benefits notably, with evacuation time costs dropping from 272 s to 206 s. These results quantitatively validate the operational efficacy of the proposed drone intervention. By providing real-time, unambiguous routing directives, the drone effectively eliminates the need for panicked passengers to blindly search for viable exits in a complex, hazardous environment. Consequently, evacuees can bypass severe congestion bottlenecks and navigate toward safe zones much more directly and rapidly, thereby securing critical life-saving margins.

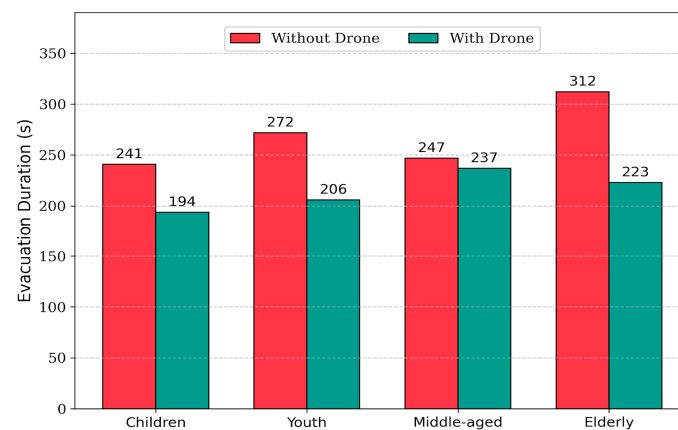


Figure 12. Evacuation Duration by Demographic Group (Familiarity = 0.25).

4.3.4. Safety Assessment and Dynamic Evacuation Efficiency

To comprehensively assess the safety dynamics and micro-level throughput capacity during the evacuation, we quantify the operational efficiency by analyzing the relative rate of change (i.e., the dynamic evacuation rate). Under the most critical scenario—where the spatial familiarity (F_{am}) is merely 0.25—the smoothed instantaneous evacuation rate $R(t)$ is mathematically defined in Equation (5):

$$R(t) = \left(\frac{N(t - \Delta t) - N(t)}{\Delta t} \right) \Big|_{F_{am}=0.25} \quad (5)$$

where $N(t)$ represents the number of remaining pedestrians in the station at moment t , and Δt defines the observation time window (e.g., a 15 s sliding window) used to filter out micro-fluctuations and capture the macroscopic throughput trend.

Figure 13 displays the comparative dynamic evolution of $R(t)$ with and without aerial guidance. In the unguided scenario, the evacuation rate exhibits a distinct “rapid rise followed by a prolonged decay” pattern. Initially (from 0 to approximately 30 s), pedestrians impulsively sprint toward the nearest visible exits, causing a brief surge in the throughput rate. However, as the localized environment rapidly devolves into chaos and congestion exacerbates at the bottleneck interfaces, the “arching” effect occurs, causing the evacuation rate to progressively collapse.

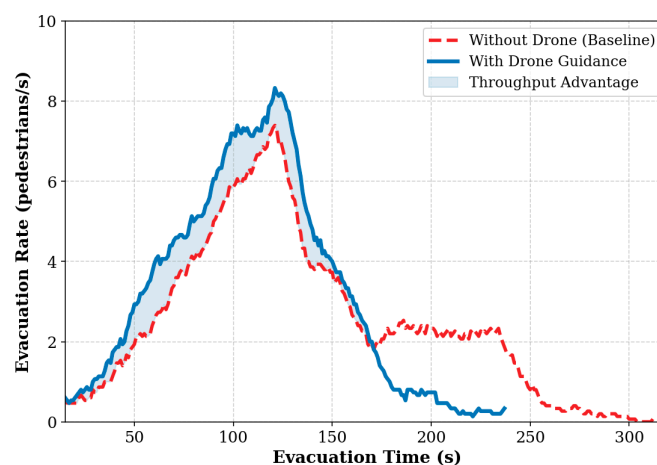


Figure 13. Comparative dynamic analysis of evacuation rates with and without drone guidance ($F_{am} = 0.25$).

Conversely, the drone-guided scenario introduces a fascinating self-organization dynamic. In the initial phase, the evacuation rate under aerial guidance is momentarily lower than the blind rush seen in the baseline. This transient phenomenon occurs because pedestrians actively alter their trajectories to follow the drone, effectively redistributing themselves away from overcrowded zones. During this phase, the crowd undergoes a critical transition from disordered clusters into structured platoons.

Once this orderly queued state is established (after approximately 30 s), the profound advantages of the drone intervention materialize. The drone guidance actively manages density levels, ensuring a highly balanced spatial distribution across all available exits and optimizing their absolute throughput capacity. Consequently, the evacuation rate under drone assistance sustains a significantly higher and more stable trajectory for the remainder of the process. Ultimately, this dynamic spatial optimization translates into a remarkable 24.0% macro-level efficiency improvement, saving 75 s of critical escape time. This compounding benefit is expected to be even more pronounced under massive crowd flows and ultra-low familiarity conditions, underscoring the indispensable safety value of dynamic drone interventions.

5. Conclusions

This study proposes a dynamic drone-assisted evacuation framework to mitigate casualty risks during subway fire emergencies. A high-fidelity digital twin platform, coupling LES (PyroSim) with an ABM (AnyLogic), was developed to capture the complex interplay between toxic smoke dispersion, bounded-rational decision-making, and crowd psychology. The core findings and contributions are summarized as follows:

- (1) **Limitations of Spontaneous Evacuation:** Higher spatial familiarity accelerates spontaneous evacuation but exhibits diminishing marginal returns. Increasing familiarity from 25% to 50% reduces evacuation time cost by 17.9%, whereas a further increase to 75% yields only a 13.7% improvement. Given the uncontrollable demographic composition in transit hubs, relying solely on spontaneous self-organization is inadequate for emergency clearance.
- (2) **Quantitative Efficacy of Drone Guidance:** Drone assistance significantly enhances macroscopic evacuation efficiency. In the critical low-familiarity scenario (25%), dynamic aerial guidance reduces total clearance time from 312 to 237 s (a 24.0% reduction). This active intervention effectively compensates for the crowd's spatial cognitive deficit, achieving an evacuation capacity equivalent to that of a highly familiar (75%) crowd.
- (3) **Micro-behavioral Restructuring:** Beyond temporal improvements, drones actively reshape crowd morphology. By providing salient visual and acoustic directives, the intervention prevents chaotic bottlenecks and transitions panicked crowds into structured platoons. This minimizes the probability of secondary stampede casualties and ensures the safe egress of vulnerable demographics.

Methodological Contribution and Future Prospects: This research establishes a data-driven paradigm for integrating Unmanned Aerial Systems (UASs) into the emergency management frameworks of smart urban transit hubs. The proposed digital twin methodology serves as a scalable, high-fidelity blueprint for systematically pre-evaluating complex evacuation interventions in a risk-free virtual environment. Moving forward, future studies will focus on developing cooperative, multi-drone routing algorithms resilient to severe smoke-induced visibility constraints. Furthermore, to deepen the microscopic realism of our agent-based framework, we plan to incorporate empirical physiological stress data derived from Virtual Reality (VR) panic experiments, thereby enabling a more profound calibration of pedestrian path-choice behaviors under extreme hazard conditions.

Author Contributions: The authors confirm contributions to the paper as follows: data collection: R.Q., Y.Y. and W.L.; study conception and design: R.Q. and W.L.; analysis and interpretation: R.Q. and Y.Y.; draft manuscript preparation: R.Q., Y.Y. and W.L. All authors have read and agreed to the published version of the manuscript.

Funding: The authors are supported by the 2025 Suzhou Science and Technology Research Project (Key Core Technology Breakthrough) (Grant No. SYG2025046).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: Author Weike Lu was employed by the company Jiangsu JD-Link International Logistics Co., Ltd., as a postdoctoral researcher. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SFM	Social Force Model
FDS	Fire Dynamics Simulator
CO	Carbon Monoxide
CA	Cellular Automata
ABM	Agent-Based Model
LES	Large Eddy Simulation

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