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Digital-twin enabled evacuation to improve individual and community resilience of building occupants against indoor Fires: Framework and route-finding algorithm

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A R T I C L E I N F O

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A B S T R A C T

During indoor fires, building occupants are typically not guided with the optimal evacuation routes according to the up-to-date situation and suffer more health damage consequently. In this study, we propose a framework for the Fire Resilience Digital Twin (FRDT), a digital-twin enabled evacuation guidance system which improves the fire resilience of occupants by providing them with optimal evacuation routes in real time. The quantification metrics for real-time fire resilience of occupants were first established. Subsequently, a route-finding algorithm based on the established metrics was proposed to enable the FRDT to generate personalized evacuation routes optimized for both individual and community fire resilience, defined in terms of health damage and total evacuation time, respectively. Simulations of 500 occupants evacuating from a fire in an underground mall with and without guidance from a FRDT prototype showed that the prototype improved individual and community fire resilience by 6 %–64 % and 14 %, respectively.

1. Introduction

As the urban population in the world continues to grow and is expected to be more than doubled by 2050, the “resilience” of people and structures in urban areas has now gained international recognition as a desired ability and trait for future cities (World Bank, 2023). A universal disruption that can occur in urban areas with fatal consequences is the occurrence of fires. In 2022 alone, an estimated total of 522,500 structure fires was reported in the United States, resulting in 2910 civilian fatalities, 11,720 civilian injuries, and 15 billion U.S. dollars of losses due to direct property damage (Hall, 2023). Known as one of the UK’s worst modern structure fires, the 2017 fire at Grenfell Tower resulted in 72 fatalities (Guillaume et al., 2020). For people and structures, fire resilience refers broadly to their ability to reduce the damage they experience from fires, as well as to recover from the damage. This is in line with definitions of resilience in the general and fire contexts which trace back to the ability to ‘bounce back’ and maintain functional continuity in the face of disruption (Haimes, 2009; Himoto, 2021). Ensuring the life safety of people is generally a higher priority than property protection and business continuity during fire events, so we focused on the fire resilience of building occupants, which is typically measured in terms of casualties and fatalities, in this paper (Manes et al., 2023). Taking a more granular perspective, the damage experienced by the occupants during a fire incident in an indoor space can be quantified in terms of the adverse health effects they experienced due to their exposure to smoke, heat, and toxic fire effluents and consequently, their fire resilience can be defined in terms of the absence of such damage. The severity of the damage depends on the evacuation routes taken, in close relationship to the crowd dynamics and fire characteristics as well as collateral smoke diffusion (Huang et al., 2020; Lin et al., 2014). Thus, one way to improve the fire resilience of occupants is to provide them with real-time guidance for their evacuation so as to enable them to

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escape with minimum damage.

The existing evacuation protocol for a fire in an indoor space is not necessarily optimized for the fire resilience of the occupants. While the occupants do receive cues to evacuate, which could be a combination of siren or alarm bell, public announcements, instructions from staff members, and visual observation of others evacuating or of smoke (Fridolf et al., 2013), they are typically not informed regarding the updated conditions of the fire in real time. Upon receiving the cues to evacuate, the occupants would start to move out based on a few options: (1) adopting pre-planned routes stipulated by an emergency evacuation plan, (2) bundling and moving together with occupants whom they have social ties to, e.g., family and friends, (3) taking familiar routes, e.g., the same way they came from, or (4) pursuing unfamiliar routes following pre-installed signages (Sime, 1983, 1985). These options often lead to the occupants taking a longer time to evacuate or adopting an evacuation route with higher exposure to fire gases or heat that can lead to more damage to their health. The resilience of the occupants can be improved if there exists a continuous and clear stream of information regarding the fire and the optimal evacuation routes (OERs) determined from real-time monitoring and prediction.

Indoor spaces in urban areas are increasingly being sensorized and connected to services over the internet due to the growing popularity of smart control systems. Additionally, emerging 5G technologies such as network slicing and Device-to-Device communication can enable more reliable communication between victims and rescuers in emergency situations where conventional mobile networks or cellular infrastructure experience failure (Fang et al., 2021). Buildings equipped with sensors are expected to be commonplace in future smart cities and they should be leveraged to enhance the resilience of not only manmade systems but also man himself—the people that live in those buildings and cities. As such, it is now timely to explore the introduction of Internet of Things (IoT)-enabled dynamic evacuation guidance for improving the fire resilience of building occupants. In this paper, we propose a fire resilience digital twin (FRDT) framework as a state-of-the-art approach for enabling the aforementioned evacuation guidance. While the exact composition of a digital twin depends on the application, there is general agreement that a digital twin is a virtual representation of a physical entity that constantly reflects the actual conditions of the entity (Jiang et al., 2021; Singh et al., 2021; Tao et al., 2019). A value-added service provided by the digital twin is the execution of analytics to support decision making regarding the control of the entity. The general architecture of a FRDT comprises of (1) the physical layer which contains both the real-world entity and the disruption of interest, such as the building, people, fire, and smoke, (2) the monitoring layer where IoT sensors and surveillance cameras possibly enhanced with artificial intelligence are used for sensing, (3) the smart platform which hosts the prediction models and carries out the scenario simulations necessary for data processing and analysis, and (4) the smart services which could include not only dynamic evacuation guidance—the focus of this paper—but also the intelligent control of sprinklers, fire doors, and smoke control systems (Jiang et al., 2023) to facilitate rescue operations, using up-to-date information about the disruption and the conditions of the victims (Jiang, 2019). Overall, the FRDT aims to monitor, model, and simulate fires, as well as assess the health status of affected occupants in real time so as to generate actionable insights towards optimal responses that improve the real-time fire resilience of occupants.

Various guidance systems for dynamic evacuation during fires in indoor spaces have been proposed in previous studies, although they might not be termed digital twins or viewed through the lens of fire resilience. These systems can differ drastically in their methods to determine the OERs. For example, Ji et al. (2022) combined two agent-based modeling approaches, namely, dynamic cellular automata and potential energy field models, to determine the optimal routes. Mohammadiounotikandi et al. (2023) employed a hybrid optimization method based on evolutionary computing which incorporates the Emperor Penguins Colony and Particle Swarm Optimization algorithms, while Yan et al. (2019) used an IoT-based adaptive Ant Colony Optimization algorithm. On the other hand, Wehbe and Shahrour (2021) proposed the use of neural computing with a machine learning model trained using a database of fire and evacuation simulations. Additionally, the systems can vary in terms of the method of how the evacuation guidance is provided, for example, using adaptive signages to influence the behavior of the occupants (Cho et al., 2015; Galea et al., 2017) or relying on applications in mobile devices or wearable technology to inform the occupants about the optimal routes (Atila et al., 2018; Chen et al., 2015; Hsiao and Hsieh, 2023). Regardless of the method adopted, most studies reported improvements to the fire resilience of occupants who receive the evacuation guidance. For instance, the system proposed by Ortakci et al. (2016), which interacts with occupants through a smartphone application, managed to reduce the average and maximum temperatures experienced by the occupants despite increasing their evacuation distances. Zhao et al. (2022) showed, through Virtual Reality experiments, that adaptive signages can shorten both the evacuation time and distance as well as reduce the health damage and stress experienced by occupants.

Currently, dynamic fire evacuation systems do not provide personalized real-time guidance to occupants because they are not designed to track the health damage of the occupants individually during a fire. Moreover, in deciding on the evacuation routes, they do not consider the tradeoff between the heath damage of an individual and the evacuation efficiency of the community, i.e., the population of occupants evacuating from the fire. The implication of this tradeoff manifests in crowded multi-exit spaces where occupants adopting evacuation routes to minimize their individual damage could end up crowding certain areas and increase the total evacuation time and overall damage of all occupants. Thus, the aim of this paper is to present a framework for a FRDT that combines real-time monitoring of the indoor environment and occupants, prediction of the tempo-spatial distribution of fire hazards, and route-finding to provide dynamic evacuation guidance to building occupants in the event of indoor fires to improve their real-time fire resilience. Specific to the FRDT, evacuation guidance involves communicating personalized OERs, which are based on real-time individual and community fire resilience and their tradeoff, to the occupants regularly during fire evacuation. To enable such functionality for the FRDT, we propose a novel cellular automata-based route-finding algorithm that generates evacuation routes which are optimized for both the individual fire resilience of occupants, defined in terms of health damage, and the community fire resilience, defined in terms of total evacuation time. To the authors' best knowledge, most of the digital-twin applications for fire evacuation reported in the literature (e.g., Ding et al., 2023; Han et al., 2024, 2020; Kim et al., 2024) do not consider simultaneously the measures of individual and community fire resilience, provide guidance only at the start of the evacuation process, and do not track the routes travelled by and thus the health 'damage' of the occupants on the individual level. Therefore, the FRDT framework contributes to the advancement of such applications as it assesses individual and community fire resilience of the occupants together in the planning of optimal evacuation routes, and continuously assesses occupant locations and fire states during the evacuation process and uses the new information to generate updated optimal evacuation routes.

As proof of effectiveness of the framework and algorithm, fire and evacuation simulations were conducted for a case study of an underground mall and the fire resilience of the occupants were compared for the scenarios with and without a prototype of the FRDT implemented. Underground spaces are of particular interest in evacuation research because they usually have narrow escape passages which facilitate the quick formation of evacuation bottlenecks that can be life threatening in fire events (Li et al., 2022). Moreover, the problem of smoke exposure of occupants during fires tends to be magnified in underground spaces because they are highly enclosed, with the directions of smoke flow and occupant evacuation typically coinciding (Cui et al., 2023).

The remainder of the paper is organized as follows. In Section 2, we discuss the concept of real-time fire resilience of building occupants and the metrics for its quantification on the individual and community level which are used in the FRDT for route-finding. In Section 3, the FRDT framework is presented together with the novel route-finding algorithm that is motivated by the objective of optimizing both individual and community fire resilience. In Section 4, we describe the case study site and the fire and evacuation scenarios which were used in the agent-based simulations to evaluate the effectiveness of the FRDT framework and resilience-based route-finding algorithm. In Sections 5, 6, and 7, we present the results of the comparative simulations, discussion, and conclusion of the study, respectively.

2. Quantification of real-time fire resilience of building occupants

Since the services provided by the FRDT are based on the fire resilience of building occupants, it is pertinent that we first establish the concepts and quantitative metrics for real-time individual and community fire resilience of building occupants that were adopted in this paper before we introduce the FRDT framework. Generally, the real-time resilience of systems can be evaluated using metrics that are defined as functions of time such as those discussed in Tan et al. (2023). Correspondingly, we propose the definition and quantification of the real-time individual fire resilience of building occupants to be based on their health “performance” at various time instants or periods during the fire event. The metrics for the occupant’s real-time health “performance” can be defined as the doses of asphyxiants and heat that were received over the time period of interest since the main hazards in a fire that threaten an occupant’s life are established to be smoke, toxic gases, and heat in the field of fire safety (Purser and McAllister, 2016). Drawing on the terminology used for performance-based resilience metrics, we define the loss of resilience $\Psi^n_{loss}(t_e)$, the impact $r^n(t_e)$, and the disruption duration T^n_d of the n th occupant engaged in fire evacuation as follows:

$$\Psi^n_{loss}(t_e) = \int_{t_s}^{t_e} d^n(t)dt \tag{1}$$

$$r^n(t_e) = \max_{t\in[t_s,t_e]} d^n(t) \tag{2}$$

$$T^n_d = t^n_{de} - t^n_{ds} \tag{3}$$

where t_s and t_e are the starting time and ending time, respectively, of the period of interest, $d^n(t)$ is a measure of the damage to the health of the nth occupant at time instant t which could be formulated as the instantaneous exposure to asphyxiants (ppm v/v) or heat (kW/m^2), and t^n_{de} and t^n_{ds} are the time instants when the nth occupant is first exposed to asphyxiants and heat above ambient levels and when he or she reaches a safe area such as an exit, respectively. To illustrate the generalizability of these real-time resilience metrics to any system and our hypothesis on how digital twins can affect these metrics, Fig. 1 shows the expected damage curves of a general system experiencing disruption under the scenario where a digital twin for improving resilience is implemented and under the baseline scenario without the digital twin as well as the differences in the values of the real-time resilience metrics between the two scenarios at a particular time instant.

To ensure the life safety of the occupants, their real-time individual fire resilience should be evaluated in relation to elasticity thresholds pertaining to their health “performance”. In this study, we considered three such thresholds, namely, the points at which a further dose of (1) asphyxiants or (2) heat received by the occupants can induce incapacitation and (3) more visual obscuration can lead to serious impediment to the occupants’ evacuation. We adopted the established concepts of Fractional Effective Dose (FED) and Fractional Effective Concentration (FEC) from the literature of fire protection engineering as a means to

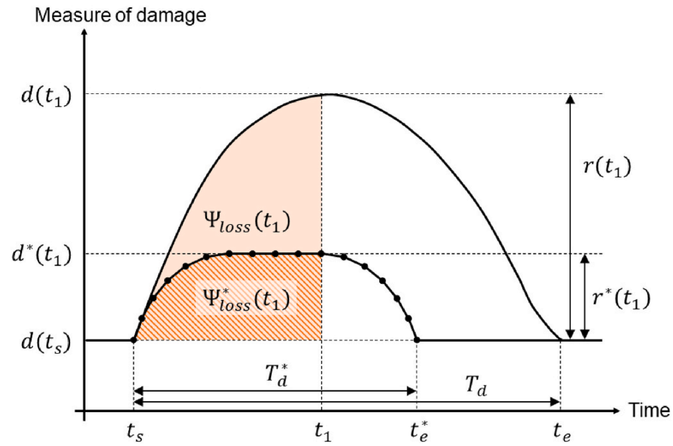

Fig. 1. Curves measuring damage of a general system with and without a digital twin implemented. The real-time metrics of loss of resilience $\Psi_{loss}(t)$, impact $r(t)$, and disruption duration T_d of the system are illustrated. The superscript * indicates the metrics and measures for the scenario with digital twin. t_s and t_e are the time instants at which the system first deviates from and recovers back to its baseline state which could be defined in terms of a measure of damage (as shown here) or performance while t_1 is an arbitrarily sampled time instant to demonstrate the real-time characteristic of $\Psi_{loss}(t)$ and $r(t)$.

compare the real-time resilience metrics, $\Psi^n_{loss}(t_e)$ and $r^n(t_e)$, against the three thresholds as they are reported in the literature (Purser and McAllister, 2016). The real-time FEDs and FEC for the abovementioned thresholds can be written as:

$$FED^n_{apxt}(t_e) = FED^n_{CO}(t_e) + FED^n_{HCN}(t_e) + FED^n_{irrt}(t_e) + FED^n_{O_2}(t_e) \tag{4}$$

$$FED^n_{CO}(t_e) = \frac{\Psi^n_{loss,COHb}(t_e)}{ET_{COHb}} = \frac{\sum_{t_s,step\Delta t}^{t_e} 3.37\times10^{-5} C^n_{CO}(t)^{1.036} V^n_E V^n_{CO_2}(t)\Delta t}{0.3} \tag{4.1}$$

$$FED^n_{HCN}(t_e) = \frac{\Psi^n_{loss,HCN}(t_e)}{ET_{HCN}} = \frac{\sum_{t_s,step\Delta t}^{t_e} C^n_{HCN}(t)^{2.36} V^n_E V^n_{CO_2}(t)\Delta t}{2.43\times10^7} \tag{4.2}$$

$$FED^n_{irrt}(t_e) = \sum_{x\in I} FED^n_x(t_e)$$

$$\text{where } FED^n_x(t_e)\ \frac{\Psi^n_{loss,x}(t_e)}{ET_x} = \frac{\sum_{t_s,step\Delta t}^{t_e} C^n_x(t) V^n_E V^n_{CO_2}(t)\Delta t}{(C_x t)_{lethal}\times 25} \tag{4.3}$$

$$FED^n_{O_2}(t_e) = \frac{\Psi^n_{loss,O_2}(t_e)}{ET_{O_2}} = \sum_{t=t_s,step\Delta t}^{t_e} \frac{\Delta t}{e^{8.13-0.54\left(20.9-C^n_{\%O_2}(t)\right)}} \tag{4.4}$$

where Δt is the time step size with the unit in minutes, the subscripts $apxt$, CO, $COHb$, HCN, $irrt$, and O_2 refer to asphyxiants, carbon monoxide, carboxyhemoglobin, hydrogen cyanide, irritants, and oxygen (exposure to low concentrations), respectively, I is the set of irritants including HCL, HBr, HF, SO_2, NO_2, CH_2CHO, and $HCHO$, $\Psi^n_{loss,x}(t_e)$ represents the accumulated health damage due to the dose of gas species x received over the period of interest, ET_x is the elasticity threshold associated with exposure to x which is herein defined as the tenability limit for incapacitation due to exposure to x, $C^n_x(t)$ and $C^n_{\%x}(t)$ are the concentrations of x at time instant t in units of ppm v/v and % v/v, respectively, at 20 °C, V_E is the volume of air breathed per minute (L/min), and V_{CO_2} (unitless) is the multiplicator term for the ventilatory stimulation by CO_2. For the derivation of the equations for dose received and the elasticity thresholds for the various gas species, as well as the supporting experimental information, the reader may kindly refer to Purser and McAllister (2016).

$$FED^n_{heat}(t_e) = \frac{\Psi^n_{loss,heat}(t_e)}{ET_{heat}} = \sum_{t=t_s,step\Delta t}^{t_e} \frac{\Delta t}{5\times10^{22}AT^n(t)^{-11.783} + 3\times10^7 AT^n(t)^{-2.9639}} \tag{5}$$

where $\Psi^n_{loss,heat}(t_e)$ and ET_{heat} are defined as above but for exposure to heat instead of asphyxiants and $AT^n(t)$ is the ambient temperature (°C) the occupant is exposed to at time instant t.

$$FEC^n_{smoke}(t_e) = \frac{r^n_{smoke}(t_e)}{ET_{smoke}} \tag{6}$$

$$r^n_{smoke}(t_e) = \max_{t\in[t_s,t_e]} OD^n(t) \tag{6.1}$$

$$ET_{smoke} = \begin{cases} 0.2 & \text{for small enclosures} \\ 0.08 & \text{for large enclosures} \end{cases} \tag{6.2}$$

where $OD^n(t)$ is the optical density per meter experienced by the nth occupant at time instant t. When the value of the FED or FEC at time instant t is more than one, the exceedance of a threshold occurs, and the occupant is predicted to experience incapacitation.

While the real-time individual fire resilience of occupants can be quantified using $FED^n_{apxt}(t_e)$, $FED^n_{heat}(t_e)$, and $FEC^n_{smoke}(t_e)$, aggregating them for all the occupants to form metrics for community fire resilience is not ideal because the aggregated metrics lack clear physical meaning and could only be used for scenario comparisons. Therefore, the total evacuation time $T_{d,total}$, defined as the time taken to reach an exit by the last occupant to exit the indoor space, is used as the primary metric for community fire resilience in this paper.

3. Fire resilience digital twin

3.1. Framework

The objectives of the FRDT are to determine personalized OERs for the occupants based on real-time individual and community fire resilience and their tradeoff, and provide dynamic evacuation guidance to the occupants during fire evacuation. The proposed FRDT framework comprising of the general digital twin components and flow of operations that are required to achieve the stated objectives is illustrated in Fig. 2. The first category of components in the framework is the sensing components represented in Fig. 2 by arrows drawn from the entities in the physical layer to the various modules in the monitoring layer. Through these components, the FRDT continuously obtains up-to-date information of the physical entities which serves as inputs for the downstream modules in the smart platform in charge of prediction and assessment. For building information that can be assumed static during fire events such as the geometry of the indoor space and the materials of the building structures and components, the FRDT should integrate a Building Information Modeling (BIM) model into its smart platform to obtain these information pre-event as necessary inputs for the fire and evacuation models that would be used during the fire events. With regard to real-time information about the fires, e.g., locations, sizes, and intensities, the FRDT would need to integrate the building's network of heat and smoke detectors, temperature sensors, and video cameras for

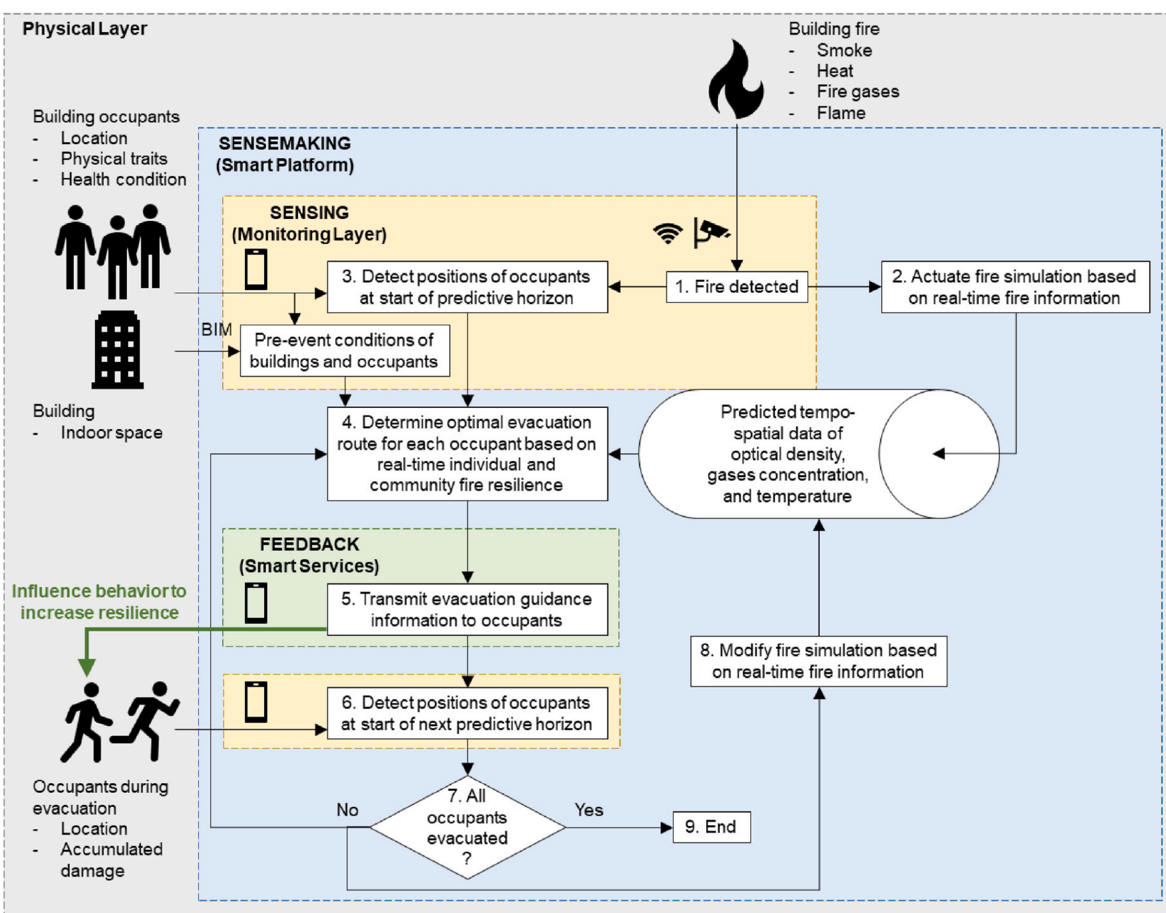

Fig. 2. Framework of the fire resilience digital twin (FRDT) for dynamic evacuation guidance. Each numbered box in the figure is termed a functional module in the smart platform of the digital twin.

detection and monitoring purposes. To track the positions of the occupants throughout the fire emergency and obtain their pre-event conditions, mobile phone applications could be employed. For example, Zou et al. (2017) proposed an indoor localization and tracking system which uses a combination of the inertial measurement unit sensors in mobile phones, WiFi fingerprinting, and iBeacon technology (for opportunistic corrections of drifting error). The proposed system has a mean localization accuracy of 0.594m.

The next category of components in the framework is the sensemaking components which are the functional modules in the digital twin's smart platform responsible for performing prediction and assessment with the aim of supporting decision making. They are represented by modules 2, 4, 7, and 8 in Fig. 2. Once a fire is detected, the FRDT starts executing a series of sensemaking operations repeatedly in cycles until all occupants have evacuated the fire site. At the start of the first cycle, the FRDT actuates a fire simulation based on the real-time fire information obtained from the sensing components to predict the tempo-spatial distribution of smoke, fire gases, and heat for a set time window, i.e., the predictive horizon (Fig. 2, module 2). Simultaneously, the digital twin runs a route-finding algorithm that uses the building information, real-time occupant positions, predicted fire hazard information and an assessment based on real-time fire resilience metrics (Section 2) to determine the OERs for each occupant (Fig. 2, module 4). A cycle of operations ends when a time period equivalent to the duration of the predictive horizon has elapsed. At the end of each cycle, sensing components are used to assess whether all occupants have successfully evacuated (Fig. 2, module 7). In the cycles following the first, the same series of operations is performed with the fire simulation updated using real-time fire information (Fig. 2, module 8).

The final category of components in the framework is the feedback components which seek to influence, adjust, or change the behaviors, conditions or states of the physical entities towards the desired objectives. In the FRDT, this component, which is represented by the green arrow pointing to the evacuating occupants in Fig. 2, communicates evacuation guidance to the occupants in real time during the fire emergency in an attempt to influence their behavior towards increased fire resilience outcomes. Since the OERs computed by the sensemaking components are personalized for each occupant, the route information communicated to each occupant is unique and the feedback channel between the digital twin and the occupants would need to be based on personal devices such as mobile phones or smart wearables.

3.2. Route optimization based on individual and community fire resilience

In this section, we present a novel route-finding algorithm that could be used in the FRDT to plan optimized personalized evacuation routes considering the real-time individual and community fire resilience of the occupants. Since the algorithm is based on a cellular automata model, we first introduce the heterogenous bosons model (HeBM) as a baseline cellular automata model for simulating evacuation and explain the modified cellular automata model that we developed for the proposed route-finding algorithm. The cellular automata approach was selected because cellular automata models have (1) high computational efficiency which makes them well-suited for large-scale evacuation simulations and parallel computing, (2) the ability to capture emergent behavior, i.e., macroscopic patterns that arise from the interactions of microscopic rules, such as lane formation, congestion, and the "faster-is-slower" effect in the context of evacuation, which might not be captured in equivalent detail by graph-based approaches and (3) the capacity to incorporate environment and disruption-associated factors as well as individual occupant characteristics and interactions which enable the simulation of diverse scenarios and the investigation of the heterogeneity of the occupant community (Li et al., 2019; Zheng et al., 2009).

3.2.1. Heterogenous bosons cellular automata model (HeBM)

The HeBM with Moore neighborhood is one way to model the evacuation movements of building occupants (Guo et al., 2015). As with all cellular automata models, the HeBM approach involves dividing the indoor area into a regular grid of usually 0.4 m × 0.4 m cells which individually represents the space an occupant in a crowd typically takes up (Burstedde et al., 2001). Each cell could either be empty or contain a single occupant, an obstacle (e.g., wall or furniture), or fire. At every discrete time step, each occupant simultaneously moves from his or her current cell to one of the eight neighbor cells, and the transition probability for such a movement can be expressed as:

$$P^n_{i,j}(t) = (1 - n_{i,j}(t))\xi_{i,j}(t)N^n(t)^{-1} \exp\Big(-k_S(S_{i,j} - S_{i0,j0}) + k_D\sum\nolimits_{k\neq n}\big(D^k_{i,j}(t) - D^k_{i0,j0}(t)\big)\Big) \tag{7}$$

where $P^n_{i,j}(t)$ is the probability of the n th occupant moving from current cell $(i0, j0)$ to a neighbor cell (i,j) at time step t, $n_{i,j}(t)$ and $\xi_{i,j}(t)$ are the occupancy parameter and obstacle parameter, respectively:

$$n_{i,j}(t) = \begin{cases} 1 & \text{if cell } (i,j) \text{ contains an occupant at time step } t \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$\xi_{i,j}(t) = \begin{cases} 0 & \text{if cell } (i,j) \text{ contains an obstacle or fire at time step } t \\ 1 & \text{otherwise} \end{cases} \tag{9}$$

$N^n(t)$ is the normalization factor to ensure the sum of the transition probabilities to all neighbor cells at time step t is equal to one. $S_{i,j}$ is the static floor field value at cell (i,j) which denotes the minimum number of cells between (i,j) and the nearest exit. k_S is the weight for the static floor field and represents the familiarity with the exit locations in the space. $D^k_{i,j}(t)$ is the value of the dynamic floor field of the k th occupant at cell (i,j) and time step t and it is a measure of the virtual traces left by the occupant whenever he or she moves through that cell (Qin et al., 2020) (occupants are not influenced by their own traces and hence the dynamic floor field of the n th occupant is not considered when computing $P^n_{i,j}$). k_D is the weight for the dynamic floor field which controls the tendency of occupants to follow the movements of others and engage in herding behavior. At each time step, $D^k_{i,j}(t)$ decays with a probability of δ and diffuses with a probability of α and these processes can be expressed, respectively, in the following formulas (Jahedinia et al., 2023).

$$D^k_{i,j}(t+1) = D^k_{i,j}(t) - \delta D^k_{i,j}(t) \tag{10}$$

$$D^k_{i,j}(t+1) = D^k_{i,j}(t) - \alpha D^k_{i,j}(t) + \frac{\alpha}{8}\Big(D^k_{i+1,j}(t) + D^k_{i,j+1}(t) + D^k_{i+1,j+1}(t) + D^k_{i+1,j-1}(t) + D^k_{i-1,j+1}(t) + D^k_{i,j-1}(t) + D^k_{i-1,j}(t) + D^k_{i-1,j-1}(t)\Big) \tag{11}$$

The combination of equations (10) and (11) can be written as (Nishinari et al., 2004):

$$D^k_{i,j}(t+1) = (1-\alpha)(1-\delta)D^k_{i,j}(t) + \frac{\alpha(1-\delta)}{8}\Big(D^k_{i+1,j}(t) + D^k_{i,j+1}(t) + D^k_{i+1,j+1}(t) + D^k_{i+1,j-1}(t) + D^k_{i-1,j+1}(t) + D^k_{i,j-1}(t) + D^k_{i-1,j}(t) + D^k_{i-1,j-1}(t)\Big) \tag{12}$$

3.2.2. Resilience-based cellular automata model

To enable evacuation route optimization that is informed by the real-time fire resilience of the occupants, we propose a modified cellular automata model based on the following heterogenous floor field which integrates the real-time fire resilience metrics explained in Section 2.

$$W_{i,j}^{n}(t) = \xi_{i,j}^{*}(t)\left(S_{i,j} + D_{i,j}^{n}(t)\right) \tag{13}$$

$$D_{i,j}^{n}(t) = k_{apxt}FED_{apxt,(i,j)}^{n}(t) + k_{heat}FED_{heat,(i,j)}^{n}(t) \tag{13.1}$$

$$\xi_{i,j}^{*}(t) = \begin{cases} \xi_{max} & \begin{array}{c}\text{if cell contains occupant, obstacle or fire OR} \\ \text{if } FED_{apxt,(i,j)}^{n}(t) \geq 1 \text{ OR} \\ \text{if } FED_{heat,(i,j)}^{n}(t) \geq 1 \text{ OR} \\ \text{if } FEC_{smoke,(i,j)}(t) \geq 1\end{array} \\ 0 & \text{if cell is exit} \\ 1 & \text{otherwise} \end{cases} \tag{13.2}$$

where $W_{i,j}^{n}(t)$ is the value of the modified floor field of the n th occupant at cell (i,j) and time step t, $S_{i,j}$ is the static floor field value defined in the same way as in the heterogenous bosons model, $D_{i,j}^{n}(t)$ is the proposed dynamic floor field value which is defined as the weighted sum of the FEDs of asphyxiants and heat of the nth occupant should he or she move to cell (i,j) at time step t, k_{apxt} and k_{heat} are the weights for the FEDs of asphyxiants and heat, respectively, and $\xi_{i,j}^{*}(t)$ is the accessibility parameter which serves to (1) prevent entry into cell (i,j) at time step t should the cell contain untenable conditions or obstructions by having an arbitrarily high value ξ_{max} such as 500, (2) guarantee movement to the cell should it be an exit by having a value of zero, or (3) allow $S_{i,j}$ and $D_{i,j}^{n}(t)$ to dictate the probabilities of movement by having a value of one. Since the purpose of the model is to determine the optimal route for fire resilience rather than to accurately simulate the natural behaviors of the occupants, the influence of evacuation traces on the movements of the occupants is omitted from the model.

3.2.3. Minimum value rule for evacuation route finding

Based on the proposed definitions of $S_{i,j}$ and $D_{i,j}^{n}(t)$ in the modified cellular automata model, a lower value of $W_{i,j}^{n}(t)$ at cell (i,j) denotes that movement to the cell would result in lower T_{d}^{n} and $\Psi_{loss}^{n}(t_e)$ compared to movements to other neighbor cells since it leads to the occupant being nearer to an exit and having lower FEDs of asphyxiants and heat. Correspondingly, the lower the value of $W_{i,j}^{n}(t)$, the higher the transition probability to cell (i,j) should be to increase the fire resilience of the occupants. A minimum value rule is thus proposed to plan the evacuation routes for optimized individual fire resilience, with the transition probability now expressed as:

$$P_{i,j}^{n}(t) = \begin{cases} \left(N_{W}^{n}(t)\right)^{-1} & \begin{array}{c}\text{if } W_{i,j}^{n}(t) \leq W_{i0,j0}^{n}(t-1) \text{ AND} \\ \text{if } W_{i,j}^{n}(t) \text{ is minimum among neighbors}\end{array} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

$N_{W}^{n}(t)$ is the number of neighbor cells around the nth occupant's position at time step t with $W_{i,j}^{n}(t) \leq W_{i0,j0}^{n}(t-1)$ and minimum $W_{i,j}^{n}(t)$ among the neighbor cells. The rule, therefore, searches among the eight neighbor cells for the cell(s) with the minimum $W_{i,j}^{n}(t)$ and designates that cell (or one of those cells, chosen randomly) as the next position in the evacuation route. This is repeated until a route to an exit is generated.

3.2.4. Resilience-based route-finding algorithm

The proposed resilience-based route-finding algorithm is designed as a two-stage algorithm. The first stage involves the computation of the tenable evacuation routes to each exit for every occupant at time t that are optimized for individual fire resilience and together form the optimal evacuation route set, $OERs_{IND}(t)$. The second stage of the algorithm uses $OERs_{IND}(t)$ as a population of potential OERs and determines the combination of personalized OERs for the occupants such that community fire resilience is optimized, generating the set $OERs_{COM}(t)$ (size equals the number of occupants) which would subsequently be communicated to the occupants individually at time t to guide their evacuation. Regardless of whether an OER to an exit for an occupant is part of $OERs_{IND}(t)$ or $OERs_{COM}(t)$, it can be expressed as $OER_{i,j}^{n,m}(t)$ where n and m refer to the serial numbers of the occupant and exit, respectively, (i,j) denotes the identity of the cell in which the occupant is currently located, and t is the current time stamp.

For an indoor space with h exits, the first stage of the route-finding algorithm uses the current positions of the occupants, the modified cellular automata model, and the minimum value rule (equations (13) and (14)) to determine the set of OERs to each exit for every occupant based on individual fire resilience. Any of these routes with FEDs of asphyxiants or heat or FEC of smoke exceeding one, i.e., incapacitation of the occupant taking these routes expected, are first removed from the set. The remaining routes form the set $OERs_{IND}(t)$ which contains OERs that are all tenable with $\Psi_{loss}^{n}(t_e)$ and $r^{n}(t_e)$ of the individual occupants below the respective elastic thresholds ET s (equation (13.2)). If individual fire resilience is the only criteria for route optimization, out of the OERs in $OERs_{IND}(t)$ that are available to an occupant, the OER with the minimum route length is selected as the optimal option since it leads to the lowest T_{d}^{n}. If the minimum route length is shared by two or more OERs, the OER with the minimum $D_{i,j}^{n,m}(t_e)$ (equation (13.1)) is then selected as the optimal option out of those. This results in the set $OERs_{IND}^{*}(t)$ which contains a single OER per occupant.

After $OERs_{IND}(t)$ is obtained from the first stage of the route-finding algorithm, the second stage proceeds to generate $OERs_{COM}(t)$. The strategy taken to optimize $T_{d,total}$, the metric for community fire resilience (Section 2), is to reduce unbalanced utilization of exits by directing occupants from congested exits to other exits which are less utilized. A simulation-based approach inspired by Gao et al. (2020) that uses the modified cellular automata model is adopted. The notations and pseudocode of the algorithm for determining the OERs considering both individual and community fire resilience are illustrated in Tables 1 and 2, respectively. The algorithm runs cellular-automata simulations with parallel updating and occupants moving according to preassigned OERs to compute $T_{d,total}$. In the event of conflicts in movements, i.e., two or more occupants moving to the same destination cell at the same time instant, only one of those occupants would be randomly selected to make the move while the others remain in their source cells. Given this

Table 1
Notations used in the route optimization algorithm.

Symbol	Description
m	Serial number of an exit, $m = 1, 2\ldots h$
h	Total number of exits in indoor space, $h \geq 2$
bn	Serial number of simulation batch, $bn = 1, 2\ldots bn_{lim}$
bn_{lim}	Upper limit for the number of simulation batches allowed
$\overline{T}_{d,m}^{bn}$	Average evacuation time of the m th exit (i.e., time taken to reach the m th exit by the last occupant to evacuate using that exit) in the bn th simulation batch
$\overline{T}_{d,total}^{bn}$	Average total evacuation time in bn th simulation batch: $\overline{T}_{d,total}^{bn} = \max\left\{\overline{T}_{d,1}^{bn}, \overline{T}_{d,2}^{bn}\ldots\overline{T}_{d,m}^{bn}\ldots\overline{T}_{d,h}^{bn}\right\}$
$\overline{T}_{d,min}^{bn}$	Average evacuation time of first exit to finish evacuation in bn th simulation batch: $\overline{T}_{d,min}^{bn} = \min\left\{\overline{T}_{d,1}^{bn}, \overline{T}_{d,2}^{bn}\ldots\overline{T}_{d,m}^{bn}\ldots\overline{T}_{d,h}^{bn}\right\}$
$d\%^{bn}$	Percentage difference between $\overline{T}_{d,total}^{bn}$ and $\overline{T}_{d,min}^{bn}$, $\dfrac{\overline{T}_{d,total}^{bn} - \overline{T}_{d,min}^{bn}}{\overline{T}_{d,total}^{bn}} \times 100\%$
$d\%_{thr}$	Percentage difference between $\overline{T}_{d,total}^{bn}$ and $\overline{T}_{d,min}^{bn}$ that is deemed acceptable, i.e., threshold below which utilization of exits is considered balanced
$c\%^{bn}$	Percentage improvement between $d\%^{bn}$ and $d\%^{bn-1}$, $\dfrac{d\%^{bn-1} - d\%^{bn}}{d\%^{bn-1}} \times$ 100%, $bn \geq 2$
$c\%_{thr}$	Percentage improvement between $d\%^{bn}$ and $d\%^{bn-1}$ that is deemed acceptable
s	Number of consecutives times in which $c\%^{bn} < c\%_{thr}$
s_{lim}	Maximum number of consecutives times in which $c\%^{bn} < c\%_{thr}$ before the termination of the loop to iteratively reassign evacuation routes
$k\%$	Percentage of occupants to be reassigned evacuation routes

Table 2
Algorithm for generating $OERs_{IND}(t)$ and $OERs_{COM}(t)$, the optimal evacuation routes based on individual and individual and community fire resilience, respectively, at a particular time instant.

Stage 1: $OERs_{IND}(t)$ generation			
1:	$bn = 1$ $s = 0$ Determine $OERs_{IND}(t)$, the set of $OER_{i,j}^{n,m,bn=1}(t)$ with minimum T_d^n to each exit for each occupant using modified cellular automata model and minimum value rule		
Stage 2: $OERs_{COM}(t)$ generation			
2:	While $s \leq s_{lim}$:		
3:		Run batch of cellular automata simulations where each occupant moves according to $OER_{i,j}^{n,m,bn}(t)$; get average evacuation time results: $\left\{\overline{T}_{d,1}^{bn}, \overline{T}_{d,2}^{bn} \ldots \overline{T}_{d,m}^{bn} \ldots \overline{T}_{d,h}^{bn} \text{ and } \overline{T}_{d,total}^{bn}, \overline{T}_{d,min}^{bn}\right\}$	
4:		If $bn \geq 2$ and $c\%^{bn} < c\%_{thr}$:	
5:			$s = s + 1$
6:		Else:	
7:			$s = 0$
8:		If $d\%^{bn} \leq d\%_{thr}$:	
9:			Set of optimal evacuation routes $OERs_{COM}(t)$ = set of $OER_{i,j}^{n,m,bn}(t)$
10:			Break from While loop
11:		Identify exit f with $\overline{T}_{d,f}^{bn} = \overline{T}_{d,total}^{bn}$	
12:		Identify E_f, the set of occupants who evacuate using exit f	
13:		Identify E_f^*, the subset of E_f comprising $k\%$ of occupants with the highest T_d^n and two or more tenable $OER_{i,j}^{n,m,bn}(t)$	
14:		For each occupant in E_f^*:	
15:			Identify exit g ($g \neq f$) using the minimum T_d^n criteria, followed by the minimum $D_{i,j}^{n,m}(t_e)$ criteria if needed
16:			$OER_{i,j}^{n,m,bn+1}(t) = OER_{i,j}^{n,g,bn}(t)$, i.e., in the next batch of simulations, occupant is reassigned the route corresponding to exit g
17:		$bn = bn + 1$	
18:		If $bn > bn_{lim}$:	
19:			Break from While loop
20:	While end		
21:	If $d\%^{bn} > d\%_{thr}$:		
22:		Set of optimal evacuation routes $OERs_{COM}(t)$ = set of $OER_{i,j}^{n,m,bn}(t)$ with minimum $\overline{T}_{d,total}^{bn}$ out of the batches (the minimum $d\%^{bn}$ criteria is subsequently used if there is a tie between batches).	

stochastic nature of the simulations, each simulation should be run multiple times in a batch. The batch-averaged evacuation times would then be considered for optimization which involved iterative reassignment of OERs for a set proportion of occupants with the highest T_d^n.

4. Case study

4.1. Evacuation scenarios and simulations

To show proof of effectiveness of the FRDT framework and resilience-based route-finding algorithm, the fire resilience of the occupants in two evacuation scenarios (baseline (*BL*), *FRDT*) were compared using simulations of a fire event in an underground shopping mall (Fig. 3). In the baseline scenario *BL*, the evacuation of the occupants was simulated using the HeBM (Section 3.2.1.) with parameters referenced from Zhu et al. (2016) and Nishinari et al. (2004) (Table 3). The evacuation simulation based on the HeBM represents the expected behavior of occupants who are uncertain about the site layout and the distribution of the fire hazards and exhibit herding behavior. We noted that the HeBM could simulate occupants moving away from an exit even though the exit is in the vicinity and view of the occupants due to the influence of the dynamic floor field. To prevent these unrealistic 'backtracking' movements, the HeBM implemented in scenario *BL* was modified by having the k_D and $D_{i,j}^k(t)$ variables removed from equation (7) and k_S set to a value of four when the occupants were located in exit-viewable cells, i.e., cells near an exit where occupants have line of sight to the exit (defined on a per site basis). This modification removes the influence of virtual traces left by occupants in the exit-viewable regions (Fig. 4).

In the digital twin scenario *FRDT*, the occupants were instead simulated to evacuate according to the up-to-date OERs communicated to them individually every 30s by a FRDT. This time interval of 30s is selected for illustrative purposes for the case study considering that it is a fraction of the average total evacuation time of approximately 90s for the setting chosen. To the best of the authors' knowledge, there has been no studies evaluating the reception of occupants to different update frequencies of evacuation instructions and, hence, the time interval of 30s between different instructions (i.e., potential redirection to another exit) was assumed to be sufficiently long such that the evacuating occupants will not experience information overload and confusion. From preliminary cellular automata simulations, we observed that if the occupants move strictly according to the computed OERs, they would queue to reach specific cells in their respective routes despite the presence of adjacent empty cells through which they could move parallel to their routes unobstructed. To reduce this unrealistic queuing behavior, the occupants were allowed in the evacuation simulations of the *FRDT* scenario to move into empty cells that are in the neighborhood of any cell in their respective OERs, reflecting the ability of occupants to make

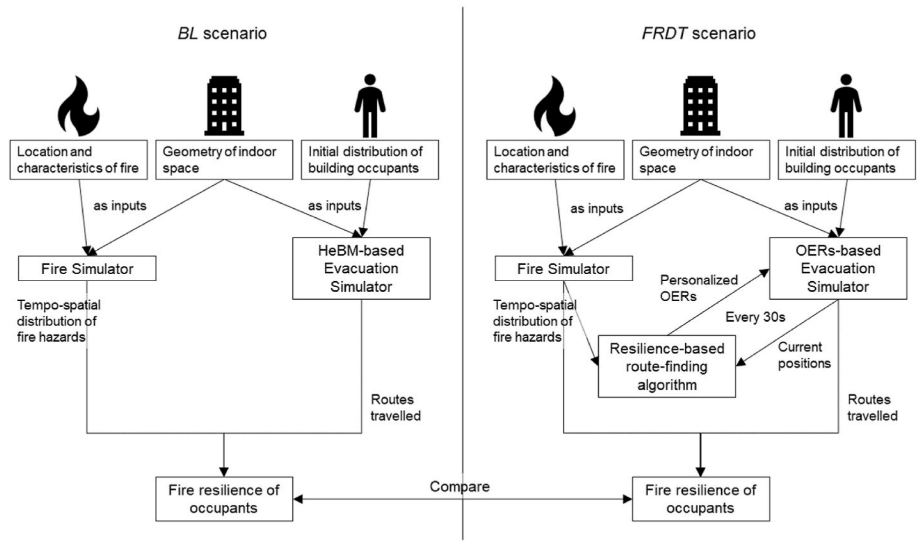

Fig. 3. Flowcharts of the comparative simulations for scenarios *BL* and *FRDT*.

Table 3
Parameters of the models used in the evacuation simulations.

Parameter	Value	Parameter	Value
HeBM		*Resilience-based cellular automata model*	
k_S	0.8	k_{apxt}	1
k_D	0.2	k_{heat}	1
δ	0.2		
α	0.2	*Resilience-based route-finding algorithm*	
		Number of simulations per batch	3
		bn_{lim}	20
		$d\%_{thr}$	10 %
		$c\%_{thr}$	10 %
		s_{lim}	15
		$k\%$	5 %

'lane changes' while following the routes on their mobile applications.

Evacuation simulations for both scenarios *BL* and *FRDT* were implemented in the Python programming language using the cellular automata approach. For the *FRDT* scenario simulations, prototype sensemaking components intended for the smart platform of a FRDT (modules 2–7 in Fig. 2) were developed in the Python programming language to execute the proposed resilience-based cellular automata model and route-finding algorithm (parameters listed in Table 3). To replicate in those simulations the flow of operations of a FRDT (Fig. 2), the Python program in charge of sensemaking and route-finding was connected to both a fire simulator (Section 4.2) and the cellular automata-based evacuation simulator (also implemented in Python) as shown in Fig. 3.

4.2. Underground shopping mall

The case site selected is an underground shopping mall located in Beijing, China, referenced from Wang et al. (2021). The indoor space is 80 m × 80 m × 4 m (length × width × height) and contains 19 big restaurants, 16 small restaurants, and a supermarket located in the center (Fig. 4). The mall has four exits with dimensions of 3 m × 4 m (width × height) and each restaurant has an exit of 1.1 m × 2.2 m (width × height). Since the layout of the ventilation system was not available, we modelled evenly-spaced 0.6 m × 0.6 m ventilation vents on the ceiling while ensuring each restaurant has two vents, one for air supply and one for air return. All the walls and floors were modelled to be 0.13 m thick and their materials were set as gypsum and ceramic tiles, respectively. The furniture in the restaurants was made of yellow pine whereas the commodity shelves and cashier counters were made of steel. To simplify the cellular automata simulations of evacuation, the chairs in the restaurants were not modelled. For both scenarios, 500 occupants were simulated, and their initial distribution are shown in Table 4 and Fig. 5, in accordance to Wang et al. (2021) who determined the numbers based on site observations and interviews.

4.3. Fire simulation

A fire event in the underground shopping mall was simulated using PyroSim (Thunderhead Engineering, Manhattan) which provided a visual interface for operating Fire Dynamics Simulator (FDS), a large-eddy simulation software that focuses on smoke and heat transport from fires, developed by the National Institute of Standards and Technology of the United States Department of Commerce (McGrattan et al., 2013). A 3D model of the mall and a mesh of the space comprising of 400,000 cells were created in PyroSim, with each cell measuring 0.4 m × 0.4 m × 0.4 m to match the dimensions of the cells used in the cellular automata models and enable easier transfer of information between the fire and evacuation simulations.

The location of the fire was set within a big restaurant as shown in Fig. 4 according to the worst-case-scenario hypothesis as explained in Wang et al. (2021). The size of the fire source was set at 2 m × 2 m and the chemical reaction was set as a polyurethane combustion reaction (see Table 5 for settings). The ventilation system was assumed to stop operating in the event of a fire to prevent the spread of fire and fire gases that could be induced by normal, i.e., non-emergency, modes of ventilation (Svensson, 2005). To simplify the simulation, no pyrolysis and combustion processes were defined for furniture outside the designated fire location. 2D slices of temperature, optical density, and mass fractions of carbon monoxide, carbon dioxide, hydrogen cyanide, and oxygen at a height of 1.5 m were outputted every 3 s during the fire simulation. These predicted tempo-spatial information of fire hazards were used as inputs for the resilience-based route-finding algorithm and also used in conjunction with the routes travelled by the occupants to calculate their FEDs (Fig. 3). In the comparative simulations for scenarios *BL* and *FRDT*, the fire simulation was assumed to be representative of a real evolving fire event in the building and we deem this acceptable as the case study is for illustrative purposes only. An investigation of the reliability of the FDS tool, its integration with real-time fire information, and the validation of the specific simulations conducted are neither within the scope nor the intentions of this study.

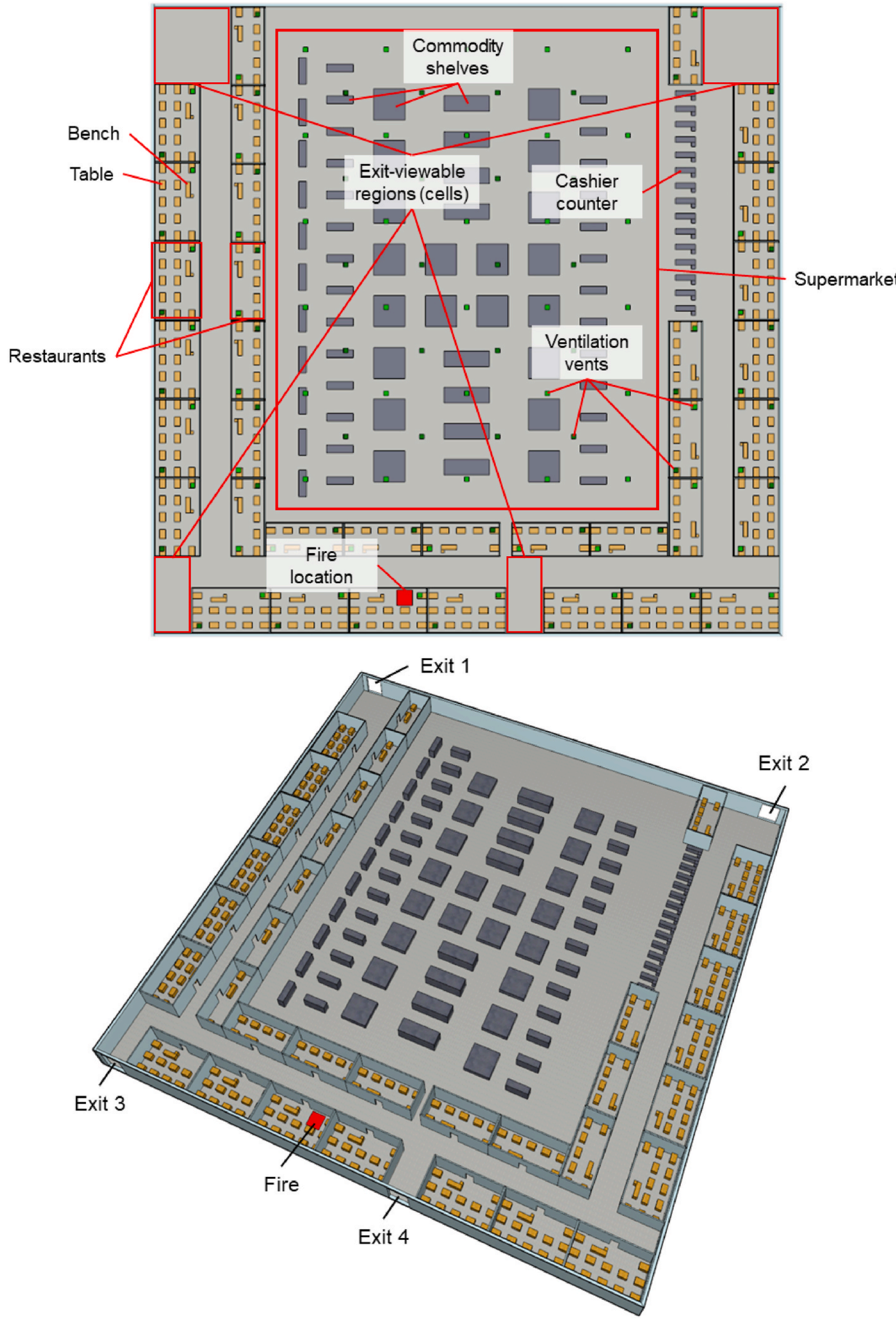

Fig. 4. Top view and angled view of the underground shopping mall.

Table 4
Initial distribution of occupants in the different areas of the mall.

Area	1	2	3	4	5	6	7	8	9
Population	30	50	60	40	60	80	40	70	70

5. Results

5.1. Effect of FRDT on fire resilience of occupants

Comparing the simulation results from scenarios *BL* and *FRDT* shows that the dynamic evacuation guidance provided by the FRDT prototype resulted in the community fire resilience of the occupants improving in terms of $T_{d,total}$, total FED for asphyxiants, and total FED for heat, with these metrics for damage reduced by 14 %, 40 %, and 98 %, respectively (Fig. 6). This improvement in $T_{d,total}$ from 101.4s to 87.6s could be attributed to two factors. First, the route-finding algorithm in the FRDT prototype actively reduced $T_{d,total}$ by considering the evolving congestion phenomena at the site and reassigned the target exits of occupants whose current evacuation routes account for the highest T_d^n in the community (the red circles in Fig. 7 show this reassignment in action). In the simulations for both scenarios, exits 2 and 4 were utilized by the most occupants and the congestion that occurred at the supermarket cashier counters near the former and at the narrow corridor between two restaurants near the latter (Fig. 7) were accounted in the route-finding algorithm. Second, the occupants in scenario *FRDT* moved towards their nearest exits at a faster speed than in scenario *BL* because they were provided with evacuation routes to adopt, thereby reducing

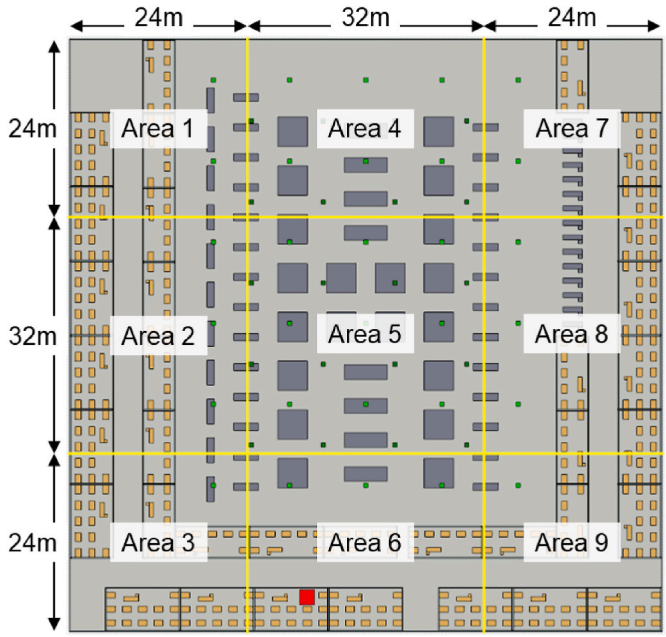

Fig. 5. Different areas of the underground shopping mall.

Table 5
Parameters for the polyurethane combustion reaction. Values with asterisks were referenced from Liu et al. (2023).

Parameter	Value
Fuel species chemical formula	$C_{25}H_{42}O_6N_2$
CO yield (kg/kg)	0.21422*
Soot yield (kg/kg)	0.15*
HCN yield (kg/kg)	0.01254*
Specific heat (kJ/(kg·K))	0.045*
Heat of combustion (kJ/kg)	24000*
Radiative fraction	0.514
Heat release rate per area (kW/m^2)	1000

haphazard movements arising from a lack of knowledge of the site or herding tendencies. While total FEDs—sums of the individual FEDs—do not have direct physiological significance, the lower values in scenario *FRDT* represent that the evacuation guidance provided by the digital twin reduced the aggregated damage experienced by all the occupants.

Comparisons of individual fire resilience between scenarios *BL* and *FRDT* were conducted for occupants who evacuated from different exits in the two scenarios. These occupants adopted significantly different evacuation routes in the different scenarios and, therefore, the comparisons would be appropriate in elucidating the effect of the evacuation guidance provided by the FRDT on individual fire resilience. The simulation results support the hypothesis that most occupants will have higher individual fire resilience, i.e., reduced health damage, in the scenario that they adopt the OERs generated by the FRDT compared to the scenario where they search for the nearest exit without the up-to-date knowledge of the fire event possessed by the digital twin. The improvements in individual fire resilience, reflected in the percentage improvements in the individual FEDs for asphyxiants (6 %–64 %) and heat (15 %–63 %) (Fig. 6), are expected since the routes generated by the FRDT were informed by predictions of the tempo-spatial distribution of fire hazards and congestion. However, declines in individual fire resilience, reflected in the negative percentage improvements in the individual FEDs for asphyxiants (9 %–118200 %) and heat (8 %–55 %), were also observed for a few occupants. This is because the route-finding algorithm assigned routes resulting in suboptimal individual FEDs to these occupants in order to optimize $T_{d,total}$ for the community.

5.2. Effect of optimizing routes based on individual fire resilience only and on both individual and community fire resilience

To elucidate the effect of the first and second stages of the route-finding algorithm on the fire resilience of occupants, the individual and community fire resilience metrics of the occupants who were simulated to adopt $OERs^*_{IND}(t)$ and $OERs_{COM}(t)$ were compared. Since the route-finding algorithm was repeated every 30s as part of the dynamic evacuation guidance provided to occupants in scenario *FRDT* and all occupants evacuated before 90s in the simulations, comparisons were done for $OERs^*_{IND}(t)$ and $OERs_{COM}(t)$ computed at 0s, 30s, rand 60s which are the starting times of the respective 30s intervals.

From 0s to 30s of the simulations, when the occupants adopted $OERs_{COM}(t)$ instead of $OERs^*_{IND}(t)$, the community fire resilience as defined by $T_{d,total}$ and total FED for asphyxiants improved by 4 % and 22 %, respectively, but worsened in terms of total FED for heat by 46 % (Fig. 8). Overall, 11 occupants had different target exits in the two sets of routes. Out of these occupants, more than half of the individuals had improved individual fire resilience in terms of FED for asphyxiants, with percentage improvements of 30 %–100 %, whereas the remaining individuals had worse such resilience, with negative percentage improvements of 8 %–26 %. With regard to FED for heat, slightly less than half of the individuals had improved values, with percentage improvements of 2 %–38 %, while the rest had worse values, with negative percentage improvements of 4 %–19 %.

From 30s to 60s, occupants who adopted $OERs_{COM}(t)$ instead of $OERs^*_{IND}(t)$ had improved $T_{d,total}$ (8 %) and total FED for heat (3 %) but worse total FED for asphyxiants (323 %) (Fig. 9). Nine occupants had their target exit reassigned, which is illustrated in Fig. 7. Besides occupants 211 and 212 who had drastically increased FED for asphyxiant (percentage increase of 45817 % and 130782 %, respectively), the other seven occupants experienced percentage changes to their FEDs for asphyxiants and heat that were within the range of 1 %–13 %. It should be noted that $OERs_{COM}(t)$ comprises of only tenable evacuation routes. Hence, despite the drastic increase in FED for asphyxiant for occupants 211 and 212 when they adopt their personalized evacuation routes from $OERs_{COM}(t)$, their FED values were still below the safety threshold of 1, at 0.12 and 0.35, respectively. Even though the nine occupants were nearer to exit 2 than exit 4, the FRDT identified the former exit as having the highest evacuation time and reassigned the occupants' target exit from the former to the latter to reduce $T_{d,total}$, resulting in them travelling a longer route and having higher individual FEDs.

Between 60s to the end of the simulations, $OERs_{COM}(t)$ and $OERs^*_{IND}(t)$ were identical, indicating that $T_{d,total}$ could not be improved by reassigning target exits identified in $OERs^*_{IND}(t)$. This is expected because during the later stages of evacuation, the remaining occupants at the fire site would be located nearer to exits in general and guiding any of them to exits besides the exit nearest to them would increase $T_{d,total}$. This highlights that the second stage of the route-finding algorithm has a greater effect on the fire resilience of occupants in the earlier stages of evacuation and becomes redundant at later stages.

6. Discussion

6.1. Value of the FRDT

The FRDT is designed to inform the building occupants in real time about evacuation routes which are predicted to not only be tenable but also result in optimized individual and community fire resilience for the occupants. Since these routes are computed with the consideration of the predicted states of the fire hazards and congestion, occupants who adopt them are expected to have higher fire resilience than those who evacuate without the guidance from the FRDT. The latter occupants tend to evacuate in a more haphazard manner because they lack the insights regarding the fire event that are possessed by the FRDT. Results from the

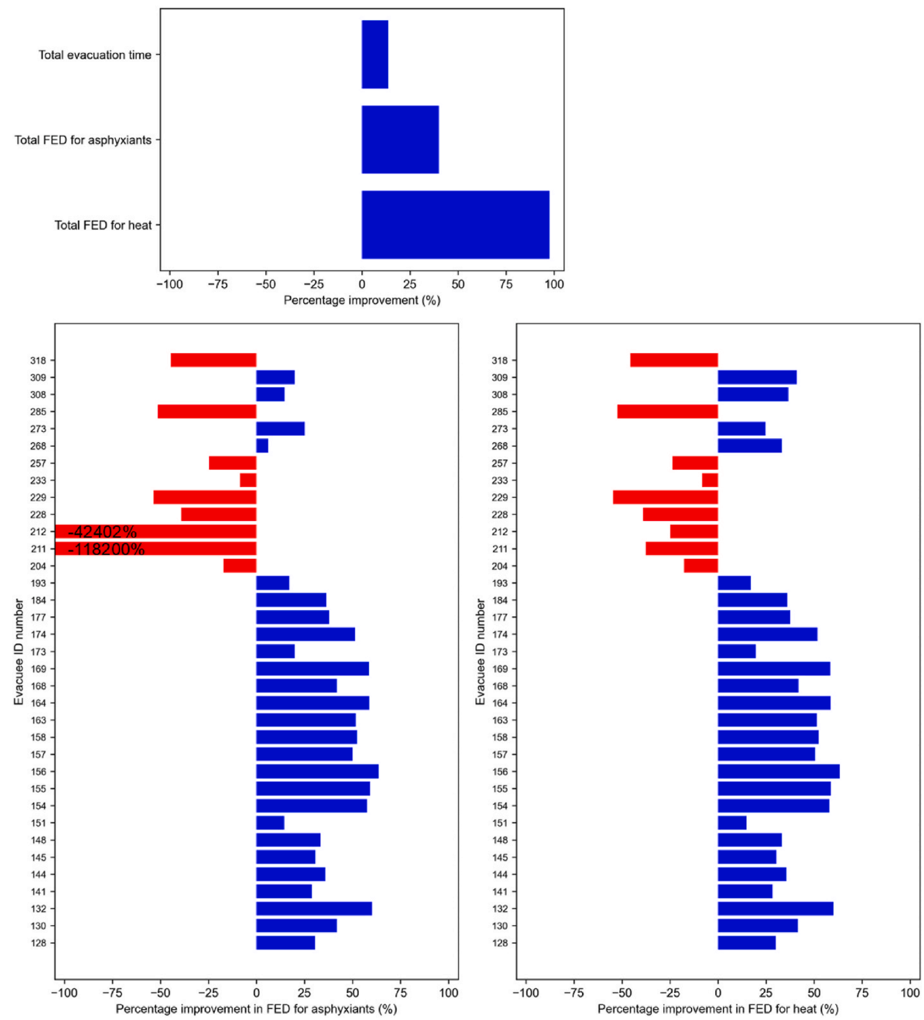

Fig. 6. Percentage improvements between scenarios *BL* and *FRDT* in the metrics of community fire resilience, namely, $T_{d,total}$, the total evacuation time, and total FEDs of asphyxiants and heat for all occupants (top), and in the metrics of individual fire resilience, FEDs of asphyxiants (bottom left) and heat (bottom right) for occupants who used different exits in the two scenarios. Scenario *BL* is the baseline for this comparison, with relative improvements and declines in the metrics in scenario *FRDT* indicated in blue and red, respectively. For example, a blue bar of 50 % means that the damage metric is 50 % lower in *FRDT* compared to in *BL*.

case study of the underground mall supported this expectation and showed that the FRDT could improve individual fire resilience of the occupants in terms of individual FEDs for asphyxiants (6 %–64 %) and heat (15 %–63 %), and community fire resilience in terms of $T_{d,total}$ (14 %). Moreover, the FRDT is cognizant of the tradeoff between individual and community fire resilience. While the second stage of the route-finding algorithm in the FRDT improves $T_{d,total}$ at the expense of individual FEDs for some occupants, this tradeoff is deemed acceptable because the algorithm is applied on a population of tenable evacuation routes. In other words, the declines in individual FEDs resulting from the optimization for $T_{d,total}$ would not cause exceedance of the elasticity thresholds pertaining to the health of the affected occupants. Consideration of the tradeoff between individual and community resilience is often difficult as the two are typically defined in different terms such as the psychological qualities and strategies for adaptation of the individual versus the social capital of the community (Chelleri et al., 2015; Kirmayer et al., 2009). As shown by the proposed two-stage route-finding algorithm, one way to account for such a tradeoff is to set one type of resilience as the primary objective and improve the secondary type of resilience with constraints defined in terms of the former.

6.2. Future work for the FRDT

The case study presented is intended to be a demonstrative example to encourage researchers, professionals, and authorities in the field of the build environment to consider (1) the real-time resilience of physical entities such as building occupants against disruption events like indoor fires in the design and maintenance of buildings, and (2) the application of digital twins for improving such resilience. Given the preliminary nature of the study, further investigation regarding the FRDT is recommended in the following areas.

Firstly, the accuracy of the evacuation model used in the FRDT could be improved by including additional considerations of the occupants. For instance, the movement speed of the occupants could be modelled to decrease as their exposures to fire gases, heat, and visual obscuration increases. One approach is to incorporate into the model the expression for the relationship between smoke density and movement speed which Purser and McAllister (2016) derived by fitting experimental data of people walking through a corridor and tunnels with irritant smoke (Frantzich and Nilsson, 2004; Fridolf et al., 2014; Jin, 1976). A more comprehensive approach would be to incorporate the expression developed by Cao et al. (2018) which describes the impacts of visibility, carbon monoxide concentration, and temperature on the occupants' movement speed. Moreover, the ability of the FRDT to track and mirror

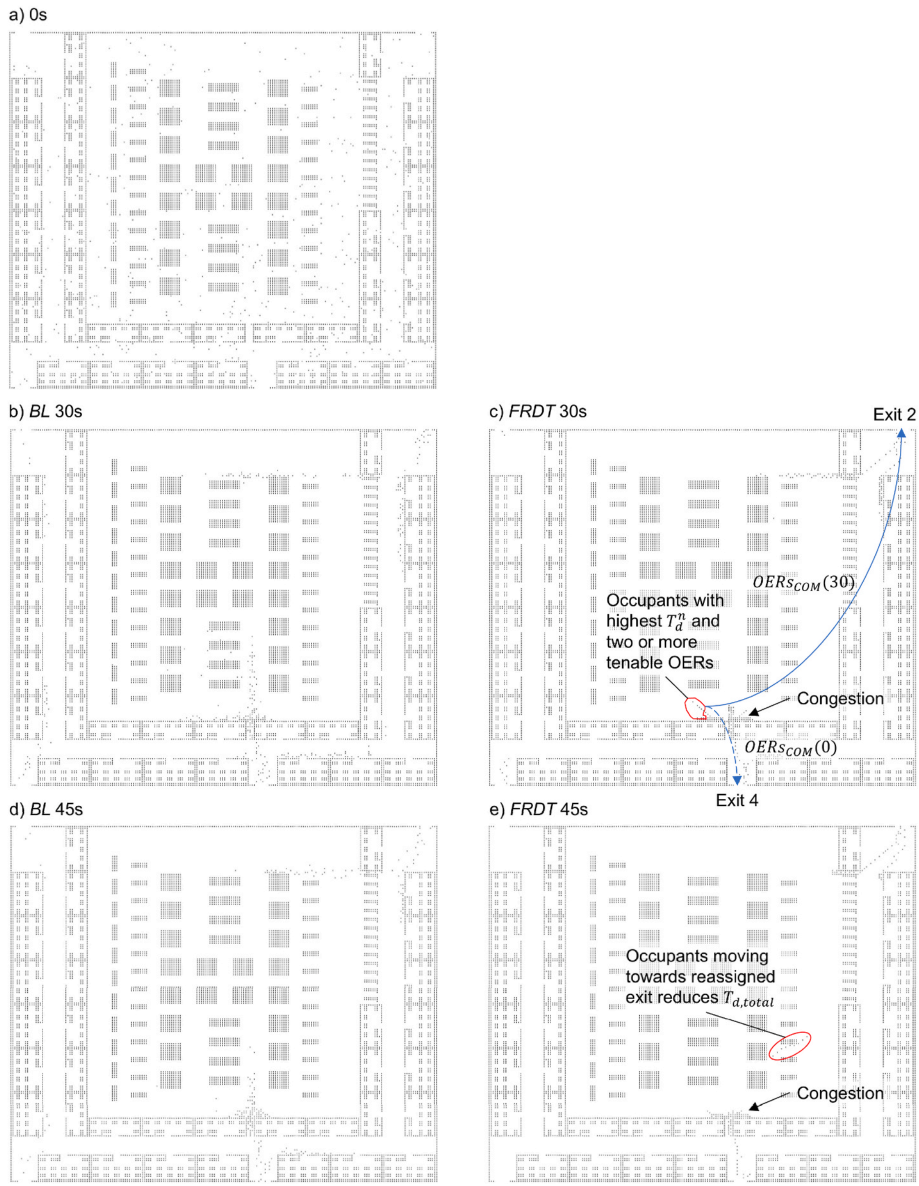

Fig. 7. Distribution of occupants in scenarios *BL* and *FRDT* at simulation time instants: (a) 0s, (b and c) 30s, and (d and e) 45s. The red circles in (c) and (e) show the nine occupants who changed their target exit from exit 4 to exit 2 after receiving the updated evacuation guidance from the FRDT at 30s to adopt $OERs_{COM}(30)$ instead of $OERs_{COM}(0)$.

the occupants individually should be capitalized by extending the resilience-based evacuation model to incorporate the heterogenous physical traits of the occupants, e.g., age, gender, and self-reported thermal tolerance, and allow for a spectrum of responses to the same fire hazards depending on the individual traits. These traits which are likely to affect the occupant's fire resilience could be collected when the mobile application for the FRDT is first installed in the mobile device, i.e., smartphone.

Secondly, the computation time of the analytics concerning the fire and occupant evacuation needs to be short such that the FRDT can provide dynamic guidance in real time. Since the focus of this study was developing the concept of real-time fire resilience for building occupants and a FRDT framework, an investigation of the technicalities regarding the implementation of the digital twin, including the speed of the models and simulations as well as the software and hardware required, were beyond the scope of the study. While FDS is widely accepted as a method for simulating the spread of a fire and its hazards (Arrizq and Setyadi, 2023; Floyd and Madrzykowski, 2024; Sun et al., 2023), its computation time is too long for real-time applications. A possible solution is to build a reduced order model using physics-based or data-driven methods (Bilyaz and Ezekoye, 2019; Black et al., 2021; Lattimer et al., 2020) or employ cloud computing with many cores (Zhang et al., 2019). Physics Informed Neural Networks have also been used successfully for tempo-spatial modelling of fires (Dabrowski et al., 2023) and reconstruction of smoke flows with sparse images (Chu et al., 2022). On the other hand, for the resilience-based route-finding algorithm, the bottleneck for computation time lies with stage one of the algorithm, i.e., the computation of $OERs_{IND}(t)$. This computation time could possibly be reduced by parallel processing where the determination of the OERs to the exits in the indoor space for each occupant is executed by multiple cores in cloud servers (Bi and Gelenbe, 2015; Zhang et al., 2020). Further reduction in computation time could be achieved by adapting the route-finding algorithm to a graph representation of the indoor space (Chen et al., 2021; Ren et al., 2023) instead of the higher-resolution grid representation as done in the cellular automata approach. In developing real-time models for the FRDT, the tradeoff between speed and accuracy

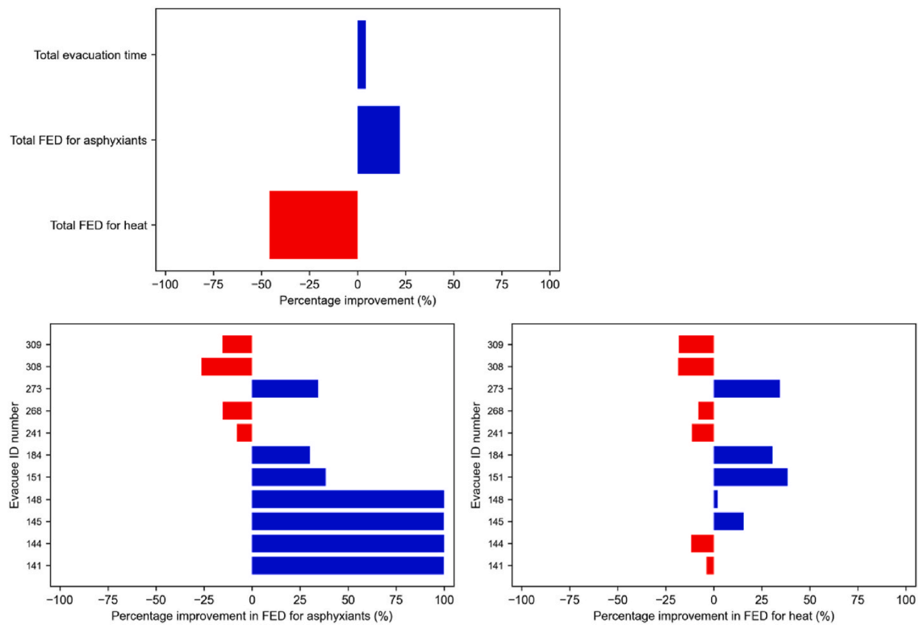

Fig. 8. Percentage improvements, comparing the routes optimized based on individual fire resilience $OERs^*_{IND}(t)$ and those optimized on community fire resilience $OERs_{COM}(t)$ at simulation time 0s, in the metrics of community fire resilience, namely, $T_{d,total}$ and total FEDs of asphyxiants and heat of all occupants (top), and in the metrics of individual fire resilience, FEDs of asphyxiants (bottom left) and heat (bottom right), for occupants who used different exits in the two sets of routes. $OERs^*_{IND}(0)$ are the baseline for this comparison, with relative improvements and declines in the metrics for $OERs_{COM}(0)$ indicated in blue and red, respectively. declines in red. For example, a blue bar of 50 % means that the damage metric is 50 % lower for $OERs_{COM}(0)$ compared to for $OERs^*_{IND}(0)$.

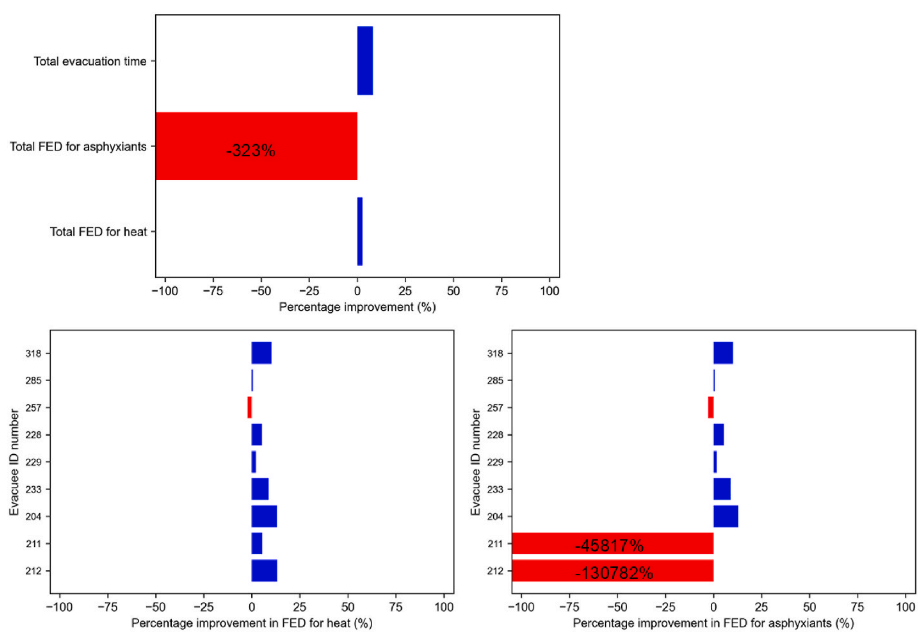

Fig. 9. Percentage improvements, comparing the routes optimized based on individual fire resilience $OERs^*_{IND}(t)$ and those optimized on community fire resilience $OERs_{COM}(t)$ at simulation time 30s, in the metrics of community fire resilience, namely, $T_{d,total}$ and total FEDs of asphyxiants and heat of all occupants (top), and in the metrics of individual fire resilience, FEDs of asphyxiants (bottom left) and heat (bottom right), for occupants who used different exits in the two sets of routes. $OERs^*_{IND}(30)$ are the baseline for this comparison, with relative improvements and declines in the metrics $OERs_{COM}(30)$ of indicated in blue and red, respectively. For example, a blue bar of 50 % means that the damage metric is 50 % lower for $OERs_{COM}(30)$ compared to for $OERs^*_{IND}(30)$.

should be evaluated. It should also be noted that some of the recent studies on AIoT-enabled digital twin systems for fire management are making significant advances in the assessment and prediction of fire states during the evacuation process. For example, Xie et al. (2025) developed a digital twin with an AutoDecoder Long Short-term Memory Neural Network that predicts the tempo-spatial distribution of temperature in a multi-floor building during a fire using historical temperature data from sensors. Zhang et al. (2024) developed a digital twin with a Transformer model that predicts the location and size of fires in tunnels using temperature data from sensors. These advances can support the future applications of the proposed FRDT framework by allowing the functional entities in digital twins to assess and predict the fields of fire hazards in real time and use them as inputs to the proposed route-finding algorithm. For more information about the software and hardware that could be used in a FRDT for data collection, transmission, storage, processing, and visualization, the readers may refer to Kim et al. (2024), Xie et al. (2025), and Zhang et al. (2024) etc.

Finally, the effectiveness of the FRDT depends on how the building occupants interact with the digital twin but studies on user-twin interactions are lacking (Ardito et al., 2018). A preliminary experiment of occupants of a university building participating in an evacuation drill while equipped with a mobile application that provided evacuation information reported that although the occupants might have limited cognitive capacity to use the mobile application under stress, the majority of them found the application to be useful to some extent (Amores et al., 2019). Moreover, the textual expressions, visualization cues, and interactive voice and vibration functions of the mobile application can be designed to improve its usability for heterogenous users (Yano et al., 2022; Zheng and Chen, 2019). Given that mobile devices remain the only practical means to provide personalized evacuation guidance to the occupants individually, training regarding the usage of the FRDT mobile application should be incorporated into fire safety courses and workshops and evacuation drills to enhance occupants' usage and trust of the digital twin during actual fires. Additionally, the occupants might not adopt the OER recommended by the FRDT if the route points them in a direction that is different from where the majority of the occupants around them are heading towards or if the route leads them to a space with some smoke despite the route being tenable (Fu et al., 2021). The implication of such psychological factors on the occupants' compliance of evacuation instructions should be further investigated. Similar to numerous navigation applications, a natural extension of the capabilities of the FRDT would be the provision of multiple OERs (e.g., one per exit if a tenable OER to the exit exists) to each occupant at the start of every control interval so that the occupants could select and follow an alternative route if they do not want to adopt the recommended one.

7. Conclusion

In this study, the concepts of real-time individual and community resilience of building occupants against fires in indoor spaces and the quantification metrics for such resilience were first developed. Then, a FRDT framework and route-finding algorithm based on the developed concepts and metrics were proposed to provide dynamic evacuation guidance to occupants in indoor fire events. The value of the FRDT is that it tracks the positions and predicts the health damage of the individual occupants and provides the occupants with personalized OERs that are informed by the damage. This function of the FRDT can be enabled by the proposed resilience-based route-finding algorithm which has a two-stage architecture. The first stage is based on optimizing individual fire resilience and generates a set of tenable OERs to exits for each occupant where the health damage due to exposure to heat or asphyxiants and the visual obscuration experienced are below the respective elasticity thresholds should the occupant adopt any of the OERs, while the second stage, based on optimizing community fire resilience, is applied to the population of tenable OERs available for all the occupants and considers the potential congestion situation to determine the optimal combination of OERs to reduce $T_{d,total}$ for the community of occupants. Results from the case study of a simulated fire incident in an underground mall provide proof of effectiveness, showing that the FRDT prototype implemented, which is based on the proposed framework and algorithm, can improve individual fire resilience of the occupants in terms of individual FEDs for asphyxiants (6 %–64 %) and heat (15 %–63 %), and community fire resilience in terms of $T_{d,total}$ (14 %). The FRDT prototype also serves as an example of how the tradeoff between individual and community fire resilience can be considered for decision making. While user-twin interactions require more investigation and further work is needed for the realization of the FRDT, we believe that the maturity of the IoT technologies and the advent of the 5G era will allow digital-twin-enabled fire resilience to move from concept to practice, with digital twin systems used to ensure resilience objectives pertaining to life safety and property protection are met during disruptive events in the build environment.

CRediT authorship contribution statement

Jonathan Koon Ngee Tan: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Shuai Zhang:** Writing – review & editing, Formal analysis, Conceptualization. **Adrian Wing-Keung Law:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization, Funding acquisition. **Sai Hung Cheung:** Writing – review & editing, Funding acquisition.

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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