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Multi-hazard hospital evacuation planning during disease outbreaks using agent-based modeling

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ABSTRACT

As different types of hazards, including natural and man-made, can occur simultaneously, to implement an integrated and holistic risk management, a multi-hazard perspective on disaster risk management, including preparedness and planning, must be taken for a safer and more resilient society. Considering the emerging challenges that the COVID-19 pandemic has been introducing to regular hospital operations, there is a need to adapt emergency plans with the changing conditions, as well. Evacuation of patients with different mobility disabilities is a complicated process that needs planning, training, and efficient decision-making. These protocols need to be revisited for multi-hazard scenarios such as an ongoing disease outbreak during which additional infection control protocols might be in place to prevent transmission. Computational models can provide insights on optimal emergency evacuation strategies, such as the location of isolation units or alternative evacuation prioritization strategies. This study introduces a non-ICU patient classification framework developed based on available patient mobility data. An agent-based model was developed to simulate the evacuation of the emergency department at the Johns Hopkins Hospital during the COVID-19 pandemic due to a fire emergency. The results show a larger nursing team can reduce the median and upper bound of the 95% confidence interval of the evacuation time by 36% and 33%, respectively. A dedicated exit door for COVID-19 patients is relatively less effective in reducing the median time, while it can reduce the upper bound by more than 50%.

1. Introduction

Facility evacuation is a complicated socio-physical process during which individuals interact with each other and the built environment under extreme conditions. The diverse mobility characteristics and needs of evacuees, especially evacuees with disabilities or restrictions, can make the evacuation process more complicated. Evacuation of individuals with disabilities is a major challenge in hospital evacuations. Every year, many hospitals are forced to evacuate their patients due to natural disasters or man-made incidents [1–3]. In the United States, due to the recent devastating hurricanes, many hospitals had to evacuate their patients. In 2005 Hurricane Rita, the University of Texas Medical Branch Hospital evacuated 427 patients in about 12 h [4]. During the 2005 Hurricane Katrina, about 1500 patients were evacuated from the Tulane’s Teaching Hospital [5], and about 111 pediatric tertiary care patients were evacuated in 12 h [6] and 121 neonates from New Orleans in 3 days [7]. Most recently, in 2017 Hurricane Irma, 35 hospitals evacuated 1900 patients [8]. In 2017 Hurricane Harvey, 1500 patients were evacuated from 45 hospitals [9]. Between 2000 and 2017, there were 154 reported major hospital evacuations in the United States, of which 71% were due to natural disasters, 16% man-made threats, and 13% incidents such as fires and chemical fumes. Compared to 1971–1999, there has been an increase in the man-made and incident events [10,11]. Considering minor incidents increases the number of evacuation events. According to the US National Fire Protection Association (NFPA), fire departments respond to an average of 5750 structure fires in healthcare facilities every year. These incidents cause an annual average of two deaths and 157 injuries [12].

The challenges of hospital evacuation deepen when there is an existing state of emergency, such as an infectious disease outbreak. In such scenarios, often preventive measures are implemented to limit interactions between patients and staff. The infectious patients and those considered as Persons Under Investigation (PUI) with pending test results are often isolated in negative pressure rooms to mitigate transmission. Furthermore, a dedicated nursing team might be assigned to the isolated units as they need special training and Personal Protective

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Equipment (PPE). These measures may delay patient flow during an emergency evacuation. With the ongoing global COVID-19 pandemic, which has impacted healthcare services for months and is expected to continue to do so for the near future, a rising concern is safe evacuation of hospitals where COVID-19 patients are hospitalized [13-17]. Past experience has shown the health risks associated with evacuation shelters during outbreaks [18]. The COVID-19 pandemic has already complicated evacuation management during disasters. In summer 2020, Arizona’s fire season coincided with a record high of COVID-19 cases, during which the reported daily new cases reached to 3500 [19]. Studies show the pandemic had adverse effects on the household capacity to respond to wildfire evacuation instructions during the fire season in Arizona [20]. Hospital evacuation also faced new challenges during the 2020 hurricane season in the US southern states [14,21,22].

Hospitals and healthcare facilities need to re-evaluate their evacuation policies and plans to ensure their adaptability with the additional complexities posed by the COVID-19 pandemic [23,24]. A common strategy in patient evacuation is evacuation prioritization, i.e., the less vulnerable ambulatory patients are evacuated first, followed by patients in critical conditions or with special constraints like infectious COVID patients. Another strategy, which requires prior coordination and preparation, is to establish a COVID-dedicated evacuation route, so that COVID patients can be evacuated separately but simultaneously with other patients. While safe evacuation of highly infectious patients is complicated as it may expose other patients and hospital staff to infection, a shelter-in-place decision also needs additional considerations for the evaluation of availability of resources and equipment for COVID-19 patients (e.g., ventilators) and hospital staff (e.g., PPE). Healthcare facilities need to ensure that they can maintain or procure supplies during the indeterminate shelter-in-place time, which can last from hours to days. Hence, the complicated decision-making process associated with hospital evacuations becomes even more complex during disease outbreaks.

Certain organizations and authorities have provided communities and healthcare facilities with guidelines to adapt a COVID-19 public health emergency policy. The US Federal Emergency Management Agency (FEMA) has published pandemic-specific operational guidelines for the hurricane season [23], requiring state and territorial government agencies to modify evacuation plans to account for travel restrictions, increased time needed for healthcare facility evacuations, and required resources in a COVID-19 environment. The scientific community has been providing the healthcare system with tools to support decision making and adapting to COVID-19 (e.g. Refs. [25-28]).

Given the scarcity of data on patient evacuation, computational modeling techniques, such as agent-based modeling (ABM), can be helpful in studying the dynamics of evacuating heterogeneous groups of patients, which in turn can support hospital decisionmakers in devising and evaluation of evacuation strategies. While machine learning models, such as neural networks, have shown promising performance across different disciplines, when it comes to hospital evacuation, they fall behind ABMs (for now) for two main reasons. First, deep learning models require big data to train. The required data to train a model for hospital evacuation should include individual and collective behavior of evacuees with heterogeneous mobility characteristics navigating under different environmental conditions. With the very limited individual and group evacuation experimental studies, data-driven models are yet underdeveloped. Second, black-box deep learning models do not provide insight on the underlying mechanisms of a dynamic process such as hospital evacuation. An advantage of microscopic computational techniques such as ABM is the ability to track the behavior of individual or groups of agents to identify the roots of certain collective outcomes. ABMs can reveal or predict the causes of potential delays in the evacuation of patients, whether it is local bottlenecks, lack of resources (nurses or equipment), or poor responders’ coordination. Hospital emergency planners use this information to revise their evacuation plans and strategies and gain insight for improvising under the uncertainties of emergencies.

2. Literature review

ABM has been used in a vast variety of applications in engineering and social sciences, specifically as a supporting tool for decision making. In the context of evacuation, ABM has been used to simulate evacuation of cities, buildings, terminals, etc. [29-32] Although such studies consider heterogeneous populations, they do not consider evacuees with special mobility needs or limitations. In this regard, there are few studies that have considered the heterogeneous characteristics of patients and evacuees with disabilities.

Christensen and Sasaki [33] developed the BUMMPEE model for hospital evacuation, in which the diversity and prevalence of disabilities among the evacuees were considered. To represent the diversity of disabilities, six criteria were identified as the mobility parameters of agents: walking speed, physical size, ability to traverse, perception, psychological profile, and assistance needs. Based on these criteria, patients were classified into seven groups: motorized wheelchair users, non-motorized wheelchair users, the visually impaired, the hearing impaired, the stamina impaired, individuals without disabilities familiar with the environment, and individuals without a physical or sensory disability but less familiar with the environment. The BUMMPEE model is used in other studies for the simulation of the evacuation of airports, stadiums, and high-rise buildings [34-36].

In another study [37], patients were categorized into four groups: (1) immobile patients who could not be moved from their beds, (2) immobile patients who could be moved from their beds but only with considerable difficulty and an associated delay, (3) immobile patients who could be moved with relative ease with assistance, and (4) mobile patients that could move on their own. Bish et al. [38] used an optimization model to develop an efficient evacuation plan for a hospital considering different types of patients. Although this study did not use ABM, it categorized patients based on their evacuation needs. In this study, patients were classified into nine groups: intensive care with ventilator, intensive care, neonatal intensive care with ventilator, neonatal intensive care, pediatric intensive care with ventilator, pediatric intensive care, other bed-bound, ambulatory oxygen-dependent, and other ambulatory.

In this study, an agent-based evacuation model was developed for evacuation simulation of non-ICU patients. In this regard, a patient classification system is developed based on mobility characteristics and needs of patients. In Section 3, the details of the agent-based model, including the patient classification framework, the path planning algorithm, the collision avoidance algorithm, the behavioral model, and the calibration and validation procedure are explained. In Section 4, the results of the evacuation simulation of the emergency department of the Johns Hopkins Hospital, considering the presence of COVID-19 patients, are presented.

3. The agent-based model

3.1. Patient classification

A common first step in developing an agent-based model is to define what an agent represents in the model. In the context of evacuation modeling, each agent represents an individual; however, different individuals have different behavior in the model. Mainly, there are two types of agents: patients and staff. While patients and staff have the mutual purpose of reaching the safe zone, staff help patients, hence, they move back and forth between the evacuation zone and the safe zone.

Although the literature on the application of ABM in evacuation simulation of hospitals is limited, there is a valuable body of work dedicated to the mobility characteristics of different groups of evacuees based on parameters such as age, gender, health status, type of mobility impairment, etc. [39,40] Accordingly, we developed a patient
classification system for non-ICU patients to be used as the basis for agent classification (Fig. 1). ICU patients are excluded in this study as their medical level of care significantly varies on a case-by-case basis. Accordingly, patients are classified into five groups: (1) visually impaired, (2) hearing impaired, (3) mobility impaired, (4) mentally impaired, and (5) non-disabled. Mobility impaired patients are further classified into five sub-groups: wheelchair users, motorized wheelchair users, stamina impaired (including crutch and walker users), high-acuity bed-bound, and low-acuity bed-bound patients. Non-disabled patients are also divided into two groups: elderly or children, and adults. The attributes of the staff agents and patient agents are listed in Table 1 and Table 2, respectively.

In Table 2, assistance indicates whether the patient agent needs help for evacuation. Those in need of assistance are the top priority in receiving help from staff agents. Those that prefer assistance can move slowly without help but move faster when being assisted. The assistance type attribute indicates whether the patient needs assistance that can be provided by anyone (staff or other volunteer patients) or only hospital staff.

The average free walking speed and size (diameter) of the agents are aggregated from the literature [39,40] and listed in Table 3. At any time, the current speed of each agent is updated according to the collision avoidance algorithm, explained in Section 3.2.

In developing the patient classification framework, certain mobility needs are considered, as listed in Table 4. The preparation time is an important factor in evacuation simulation. It denotes the time it takes for the patients and staff to start to evacuate after the alarm is raised. This delay is mainly due to two factors: event perception and patient preparation. There have been a few studies on the reaction time and preparation time during hospital evacuations for patients with different mobility needs [37,41–44]. The preparation times for bed-bound patients and wheelchair users include the average time it takes to provide the required equipment and prepare the patient for evacuation.

### 3.2. Path planning and collision avoidance

The mobility engine of agent-based evacuation models consists of two components: path planning and collision avoidance. The premise of agent path planning is that evacuees take locally optimal paths when passing through obstacles, rooms, and corridors to reach their destination [45,46]. Consequently, the path planning problem in agent-based evacuation models are mainly solved using shortest path algorithms. In this regard, the environment is represented with a graph in which the nodes represent the obstacles’ vertices, bottlenecks, and all entrance and exit doors. In graph theory, the shortest path problem is defined as finding the minimum weighted distance between two nodes in a graph. Several algorithms have been developed to solve the shortest path problem, such as the Dijkstra’s algorithm [47], the Floyd–Warshall algorithm [48,49], the Bellman–Ford algorithm [50,51], and the A* algorithm [52]. In this study, the Floyd–Warshall algorithm is used to obtain the shortest path between all pairs of nodes. While the above-mentioned algorithms perform comparably in medium-size networks, the use of the Floyd–Warshall algorithm is merely a subjective

### Table 1

| Attributes | Description | Data Type |
|------------|-------------|-----------|
| status     | 1 = idle, 2 = moving toward a patient, 3 = helping a patient, 4 = self-evacuation | categorical |
| free speed | free flow walking speed [m/s], body size (diameter) [m] | floating point number |

### Table 2

| Attributes | Description | Data Type |
|------------|-------------|-----------|
| class      | 1 = visually impaired, 2 = hearing impaired, 3 = wheelchair user, 4 = motorized wheelchair user, 5 = stamina impaired, 6 = high-acuity bed-bound, 7 = low-acuity bed-bound, 8 = mentally impaired, 9 = elderly or children (non-disabled), 10 = adult (non-disabled) | categorical |
| assistant | assistance need: 1 = none, 2 = preferred, 3 = required | categorical |
| assistant type | type of needed assistance: 1 = none, 2 = general, 3 = special | categorical |
| assistant count | number of needed assistants | integer |
| status      | 1 = idle, 2 = waiting to receive assistance, 3 = being assisted, 4 = helping another patient, 5 = self-evacuation | categorical |
| free speed | free flow walking speed [m/s], body size (diameter) [m] | floating point number |

![Fig. 1. Proposed non-ICU patient classification framework.](image-url)
knowledge can gain information from other agents based on the information sharing, have been observed and described in evacuation studies [53–56]. A number of collision avoidance algorithms have been developed for agent-based crowd simulation (e.g. Refs. [57,58]). In this study, the predictive collision avoidance model developed by Karamouzas et al. [56] is used for its simplicity and computational efficiency, in which the trajectories of all agents are extrapolated to determine possible collisions within a specific time period.

### 3.3. Social interactions

Certain social behaviors, such as grouping, herding, rescuing, and information sharing, have been observed and described in evacuation studies [59–64]. The information sharing and social behavior components in this study are adopted from a previous study conducted by Liu et al. [29].

Herding is mainly observed among evacuees unfamiliar with the environment. As discussed before, the shortest path algorithms assume that all the occupants have knowledge about evacuation paths. Although this assumption is not realistic, those occupants that do not have such a knowledge can gain information from other agents based on the information sharing and social behavior model. This implies that the unfamiliar agents will eventually gain information and follow the optimal routes but with delays and possible sub-optimal behaviors resulting from interacting with other agents. Those patient agents who are familiar with the building will follow the optimal paths to go from their initial position to the safe zone. The unfamiliar patient agents will evaluate other agents in their field of view and adopt the destination of the plurality. If no other agent is found or agents within their field of view do not have the information about evacuation routes, the agents will locate a temporary destination based on a set of rules until more information is available. These rules are as follows: (1) If an agent is in a room or corridor, it will set their destination to the closest door, or if there are exit signs, the agent will follow the direction shown by the sign. If there is no door or sign, the agent will move randomly. (2) If an agent is in a corridor, it will prioritize staircases over doors. (3) Agent will prioritize external exits over stairs and doors. (4) If an agent is on stairs, it will descend until reaching the first floor and proceed to exit the staircase. (5) Agents hold information about the room and corridors that they have visited and avoid those locations upon returning.

Agents who share a specific attribute engage in grouping behavior, for example, agents who are familiar with the environment or patients from the same agent class. When a patient who can engage in grouping and is not a member of a group encounters another patient, who is also capable of grouping, it may join the group or form a new group with other agents based on the probability function shown in Equations (1) and (2).

$$P_{\text{grouping}}(d) = \left\{ \begin{array}{ll} (1 - \omega)f(d) + \alpha \left(1 - \frac{|b_i - b_j|}{B}\right) & |b_i - b_j| \leq B \\ (1 - \omega)f(d) & |b_i - b_j| > B \end{array} \right.$$  \hspace{3cm} (1)

$$f(d) = \left\{ \begin{array}{ll} \frac{1}{\exp \left( s - \frac{d}{s} \right)} & d \leq s \\ \frac{1}{\exp \left( 1 - \frac{d}{s} \right)} & d > s \end{array} \right.$$  \hspace{3cm} (2)

where $\omega \in [0,1]$ is the importance of social interaction, $b_i$ and $b_j$ are the home-base identifiers of agents $i$ and $j$, respectively, $B$ is a user-defined constant which denotes the maximum difference between two agents for which they are still willing to group together, $d$ is the distance between two agents, and $s$ is the maximum distance agent $i$ can walk, in one time step. Agents can switch groups if they find another group with which they share a stronger social bond.

Rescuing and information sharing introduce altruism into the model. In the model, each agent is assigned an altruism probability ($P^{\text{alt}}$) which follows a normal distribution for patient agents, $P^{\text{alt}} \sim N(0.8, 0.05)$ and is set to 1 for staff agents. Regarding rescuing, if an agent, who does not need assistance for mobility and is not helping other agents, encounters another agent in its field of view who needs general assistance, based on its altruism probability will decide to approach the agent and assist in moving. When an agent is helping another patient agent, their moving speed will be set to the assistance mode according to Table 3-3. When in

#### Table 3
Free moving speed and size of the agents.

| Agent Class       | Free Speed on Floors (m/s) | Free Speed on Ramps (m/s) | Free Speed on Stairs (m/s) | Size (m²) |
|-------------------|---------------------------|---------------------------|---------------------------|-----------|
|                   | Assisted | Not Assisted | Assisted | Not Assisted | Assisted | Not Assisted |
| Stuff             | 0.69     | 1.4         | 0.9      | 0.7          | 0.7      | 0.25         |
| Visually impaired | 0.69     | 0           | 0.61     | 0            | 0.61     | 0            |
| Hearing impaired  | 1.25     | 0           | 0.9      | 0            | 0.7      | 0            |
| Wheelchair user   | 1.25     | 0.69        | 0.89     | 0.5          | 0.89     | 0            |
| Motorized wheelchair user | 1.25 | 0.89 | 0.89 | 0.7 | 0.89 | 0 |
| Stamina impaired  | 0.78     | 0.57        | 0.49     | 0.36         | 0.69     | 0.33         |
| Bed-bound         | 0.89     | 0           | 0.67     | 0            | 0.7      | 0            |
| Mentally impaired | 1.25     | 0           | 0.7      | 0            | 0.7      | 0.25         |
| Elderly (non-disabled) | 1.05 | –            | 0.7      | –            | 0        | 0.25         |
| Adult (non-disabled) | 1.25 | –            | 0.9      | –            | 0.7      | 0.25         |

4 The bed-bound class includes both the high-acuity and low-acuity patient classes.

5 Bed-bound patients occupy a $1 \times 2$ m² rectangle, which can also be modeled by two attached circular agents, each with a diameter of 1 m.

#### Table 4
Mobility needs of agents.

| Agent Class                  | Assistance need | Assistance type | Assistant count | Preparation time (sec) |
|------------------------------|-----------------|-----------------|-----------------|------------------------|
| Visually impaired            | Required        | General         | 1               | 30–63                  |
| Hearing impaired             | Preferred       | General         | 1               | 30–63                  |
| Wheelchair user              | Required        | General         | 1               | 30–100                 |
| Motorized wheelchair user    | None            | None            | 0               | 30–100                 |
| Stamina impaired             | Preferred       | General         | 1               | 30–63                  |
| High-acuity bed-bound        | Required        | Special         | 2               | 180–900                |
| Low-acuity bed-bound         | Required        | Special         | 1               | 30–100                 |
| Mentally impaired            | Required        | General         | 1               | 30–63                  |
| Elderly/Children (non-disabled) | Preferred  | General         | 1               | 30–63                  |
| Adult (non-disabled)         | None            | None            | 0               | 30–63                  |
rescuing mode, an agent can still engage in grouping or herding. For information sharing, agents assist other agents by sharing their information about the evacuation routes, location of safe zones, and impassable waypoints.

3.4. Calibration and validation

The collision avoidance algorithm presented in Section 3.2 uses a set of parameters that control the walking behavior of evacuees. The extent to which people are willing to walk close to each other depends on the size of their preferred personal space and collision prediction horizon, i.e., how far before a collision with another individual is predicted, a person will adjust its speed and trajectory. These attributes vary depending on the situation. A big group of people who are walking in an airport terminal hold a larger personal space than a group of people evacuating the same airport terminal. Therefore, the parameters of the collision avoidance algorithm are recalibrated using empirical room evacuation data [65, 66]. For the details of calibration, please refer to the supplementary appendix.

4. Evacuation simulation of an emergency department

4.1. Emergency department, Johns Hopkins Hospital

The Johns Hopkins Hospital, located in Baltimore, Maryland, is a 1000-bed academic Level 1 trauma institution. The facility includes separate emergency departments for children and adults, which see more than 100,000 patients annually. The adult emergency department (ED) consists of a total of 72 private examination rooms for patients and their families (see Fig. 2): 25 in the main ER unit, 8 in the psychiatry unit, 6 trauma care rooms, a 17-room emergency acute care unit (EACU), and 16 in the rapid assessment process (RAP) unit. The adult ED is also equipped with an on-site diagnostic radiology suite with computed tomography scan, ultrasound, and MRI capabilities.

4.2. Evacuation scenarios

The main scenario is a fire emergency outside of the hospital that can reach the premises and pose risk to the patients in the ED. However, due to the ongoing COVID-19 pandemic, the emergency evacuation strategy needs to be revised in response to the pandemic situation, moving toward a multi-hazard emergency planning. The time of the scenario is 12PM when the ED sees the greatest number of visits according to the patient service area (PSA) utilization data (see Fig. 3).

![Fig. 2. Adult ED at Johns Hopkins hospital.](image)

Fig. 2. Adult ED at Johns Hopkins hospital.

The current nurse-to-patient ratio in the ED is 1:4 or 1:5, depending on the ED unit. Although there are no laws regarding the minimum number of required nurses, professional organizations, such as the National Nurses United [67], have proposed certain nurse-to-patient ratios for different units in a hospital.

Upon initiation of each simulation, the classes of patients in each unit will be randomly selected using a multinomial distribution with equal outcome probabilities as follows: psychiatric patients consist of mentally impaired and non-disabled; main ER patients consist of wheelchair users, stamina impaired, low-acuity bed-bound, and non-disabled; EACU and trauma patients consist of only high-acuity bed-bound; RAP patients consist of wheelchair users, stamina impaired, low-acuity bed-bound, and non-disabled; triage patients consist of wheelchair users, stamina impaired, and non-disabled; COVID patients consist of wheelchair users, stamina impaired, low-acuity bed-bound, and non-disabled.

In COVID scenarios, the classes of patients in COVID units will be sampled from the COVID patient classes and not the unit-specific patient classes.

It is noteworthy to highlight that while the number of patients in each unit is the same across all the scenarios, the average number of patients from each patient class varies across the scenarios due to the size of the population of COVID patients. The underlying rationale behind this assumption is that although the non-COVID ED visits were decreased by an average of 42% early in the pandemic [68], the daily ED visits gradually increased to almost the same rates of those before the pandemic, but only due to capacity limitations, the number of non-COVID ED admissions has decreased. Furthermore, the assumption of the same total number of patients across all the scenarios would make the comparison of interventions easier.

4.3. Modeling

The main components of the ABM are described completely in Section 3. Here, the specific details for modeling the ED of the Johns Hopkins Hospital are presented.

The model was developed in NetLogo, a multi-agent programmable...
modeling environment developed by Uri Wilensky in 1999 [69]. For each unit of the ED, patients were created and positioned in the examination rooms and over the waiting area. The nurses were positioned randomly in their assigned units and their attributes were set as explained in Sections 3.1 and 4.2.

In the pre-COVID scenario, in each ED unit, the nursing team helped patients in need of assistance evacuate the hospital. Once all patients of a unit were evacuated, the nurses joined the nursing teams in other units. In the COVID scenarios, the nurses in the COVID-specific unit did not join or receive help from other nurses to keep the COVID unit isolated from other units. Although based on the implemented strategy, COVID patients may be completely evacuated after non-COVID patients, and from a modeling perspective, the evacuation of non-COVID patients can be replaced by a stochastic delay variable, there are three reasons for including the non-COVID patients in the simulations: (1) due to lack of data, there is no statistical tool available that could provide us with the probability distribution function for the total evacuation time of patients considering all the heterogeneity and complexities associated with patient evacuation; (2) from a coordination and emergency management perspective, the dynamic of patient exit rate through the evacuation process is more important than merely the total evacuation time. Decoupling (from a modeling standpoint) the evacuation of COVID and non-COVID patients would make the model useless as it would not capture the entire dynamics of the evacuation; and (3) more importantly, the utility of hospital evacuation simulation is strategy evaluation. Hospital emergency officials need to know why certain evacuation strategies may not work (what is the underlying causes of delay) in order to revise and implement more efficient strategies.

For each scenario, the simulations were repeated 1000 times to account for randomness in the variables.

### 4.4. Results

The results of the simulations for different intervention scenarios are shown in Fig. 4. In these figures, the number of evacuees left in the ED is plotted with a time step of 1 s; hence, the darker pixels show the more frequent number of evacuees at each time step over 1000 simulations. According to the results, the presence of COVID patients doubled the median evacuation time, from 26 min to 50 min. The added time due to COVID patients can be reduced through different strategies. Increasing the number of nurses from 20 to 37 reduced the median time to 32 min (Fig. 4c), i.e., only a 23% increase in evacuation time to compare with the pre-COVID scenario. Alternatively, a COVID-dedicated evacuation path resulted in a 41-min median evacuation time (Fig. 4d).

In intervention scenarios I1 and I2, COVID patients had to wait (while getting prepared to evacuate by the COVID-dedicated nursing team) for an average of 48 and 30 min, respectively, for non-COVID patients to evacuate. After this waiting time, COVID patients were evacuated with an average rate of 12.3 patients per minute. However, in intervention scenario I3, in which all patients were evacuated simultaneously while COVID patients were assigned a dedicated exit path, COVID patients were evacuated with an average rate of 0.8 patient per minute (Fig. 5).

A parameter that is used in emergency evacuation planning is the upper bound of the estimated evacuation time, i.e., the possible worst-case scenario. The histograms of total evacuation times (Fig. 6) show a highly right-skewed distribution for interventions I1 and I2, implying that more of the variance is the result of infrequent extreme deviations. The statistics of the estimated evacuation times are listed in Table 6. While intervention I2 (larger nursing team) resulted in a shorter median evacuation time, intervention I3 (COVID-specific exit door) was more...
5. Discussion

Moving toward a more resilient society, we need to adapt ourselves to the new world that the COVID-19 pandemic has created. The ongoing global pandemic has affected our lives in many ways, including the daily operations of hospitals. As the pandemic is expected to continue, there has been a rising concern over hospital operations, such as planning and responding to emergencies and disasters. Hospitals have implemented special protocols to mitigate the transmission of the coronavirus between patients and staff. While these measures are critical for the safety and health of all patients and staff, they can significantly hinder emergency operations such as evacuation.

In any imminent or ongoing disruptive event, especially a fire emergency, time is a major constraint as for the safety of the patients, the evacuation must be over by a certain time. The pre-COVID scenario shows that the hospital officials will need 19–34 min to completely evacuate the patients. However, these numbers significantly change as we consider the presence of COVID patients. Although the results show that the final evacuation time will be about 50 min, this is only the median value. For a more informed evacuation planning, hospital emergency managers are interested in learning about worst-case scenarios to incorporate flexibility and robustness in their decisions. Certainly, there are many things that can go wrong and delay the evacuation during a fire emergency, such as lack of resources, miscoordination of the responders, or secondary incidents like explosions or blocked evacuation routes due to fire or smoke. As the focus of our study is patient disability, the main source of delay in the model that is contributing to the evacuation procedure is number of patients, types of patients in need of assistance, and available human resources (nursing teams). Nevertheless, the range of estimated total evacuation time is significantly wide, especially when the COVID patients are considered.

If the only control strategy for COVID patients is prioritization (to

Table 6
Statistics of the estimated evacuation time.

| Scenario | Median [minutes] | 95% CI [minutes] | Skewness* |
|----------|------------------|------------------|-----------|
| Pre-COVID | 26               | 19–34            | −0.11     |
| I1       | 50               | 34–118           | 1.00      |
| I2       | 32               | 23–79            | 2.62      |
| I3       | 41               | 28–55            | 0.09      |

* Confidence interval.
* Zero indicates symmetry. Positive values indicate longer right-side tails than a normal distribution.
evacuate COVID patients after all non-COVID patients are evacuated), the evacuation time can take up to 2 h. The extra delay is mainly due to the number of patients in need of assistance and available number of nurses. For cases in which the relative number of high-acuity patients were high, the evacuation took a longer time. As these patients are assumed to need a team of two nurses for preparation and evacuation, and preparation takes time, a low nurse-to-patient ratio implies a longer waiting time for patients to receive assistance. One strategy to reduce this delay is increasing the size of the nursing team. Alternatively, if COVID patients are staged in the EACU, the layout of the ED can be altered such that the lobby’s exit door can be dedicated to COVID patients while other patients evacuate from the main entrance. A larger nursing team can reduce the total evacuation time to 32 min with an upper bound of 80 min (under the study assumptions). Interestingly, while the second strategy is less effective in reducing the total time (41 min), it significantly lessens the upper bound to 55 min. Therefore, if the objective is to minimize the expected median evacuation time, it will be more effective to have a larger nursing team in the ED. However, if we seek to limit the worst-case evacuation time to a certain threshold (e.g., 1 h), then having a dedicated COVID exit path is the better solution.

When comparing intervention scenarios, the cost of each intervention should be considered, as well. These costs vary across hospitals depending on the available resources, level of preparedness, and internal protocols and policies. Although cost estimation was out of the scope of this study, it is noteworthy to highlight that a larger nursing team can be costly as it needs hiring (or reassigning) 17 more nurses and the extra costs associated with training. A dedicated COVID exit path has its limitations, as well. Although the entire ED at the Johns Hopkins Hospital is equipped to be converted to negative-pressure rooms with available portable equipment for the accommodation of COVID patients, the lobby and the entrance area must be prepared to separate the COVID patients from other patients and staff as they evacuate simultaneously.

6. Conclusions

The interactions among humans and the built environment make evacuation a complex socio-physical process. This process is more complex in hospital evacuations during pandemics due to the diverse mobility needs and limitations of patients. To evaluate the efficiency of emergency and evacuation plans during pandemics, emergency teams need drill exercises, however, hospital evacuation drills are costly and disruptive. Given the scarcity of data on hospital evacuation, computational modeling and simulation can play an important role in disaster preparedness and response by providing emergency managers and decision makers with useful information and insights about evacuation under different scenarios.

Certainly, there is much room left for improvement. There are certain types of patients, such as ICU patients, that require a higher level of care during evacuations, which should be considered for a full-scale hospital evacuation study. This includes a database of available ICU beds in other hospitals. Moreover, the need for availability of specific equipment, such as oxygen tanks, ventilators, and ambulances, should also be considered. The supply and demand for equipment can affect the evacuation process. This is very critical as mainly patients in more critical conditions need such equipment, and extra delay in the evacuation of these critically ill patients can impose serious risks to their lives and the safety of the staff.

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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Appendix A. Supplementary data

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