Modeling post-shock emergency transfers with the participation of connected-and-autonomous vehicles

Taiyi Zhao[1,3], Jingquan Wang[1*], Li Sun[2,3*] & Dina D'Ayala[2]

1 Key Laboratory of Concrete and Prestressed Concrete Structure of Ministry of Education, School of Civil Engineering, Southeast University, Nanjing, China

2 Department of Civil, Environmental and Geomatic Engineering, University College London, London, United Kingdom

3 These authors contributed equally: Taiyi Zhao, Li Sun

* E-mail: wangjingquan@seu.edu.cn; li.sun@ucl.ac.uk

Abstract: This paper presents a new pathway towards the public health resilience, through the development of a principled understating on the post-hazard emergency transfer of the injured population across densely-populated urban communities, considering the deployment of connected and autonomous vehicles (CAVs). Given the influence on the system resilience of several parameters such as the number and distribution of CAVs, the initial geographic distribution of the injured and the spatiotemporal evolution of the functionality of the integrated hospital-road networks, a multi agent-based modelling (ABM) framework has been established to identify relevant patterns and bottlenecks in injured transfers across hazard-impacted urban communities. In such an ABM framework, each individual vehicle, transferring an injured inhabitant, is modelled as an independent agent, whose traveling is shaped by pre-defined behavioral attributes, while the interplay among those agents is also considered, throughout the entire transfer campaign. Based on a hypothetically catastrophic earthquake scenario, such an ABM framework is employed to model the city-scale, post-shock transfer across Tangshan city, located in one of the most earthquake-prone regions of China. The simulation outcome reveals that the information sharing with regard to the real-time functionality of the local hospital system plays a strategically crucial role, to the avoidance of uncoordinated and prolonged transfers. Furthermore, owing to their capability of intelligent route planning, the participation of CAVs can substantially bolster the rapidity and effectiveness of post-shock transfer campaigns.

Key words: Public health resilience; Post-hazard transfer; Hospital systems; Agent-based model; Connected and autonomous vehicles; Route planning

1. Introduction

Despite its significant contribution to socio-economic development, the current pace of urbanization poses challenges to the well-being of modern cities, as it is expected that by 2050, 68% of the world population will be urban (United Nations 2018). Increased population density has severe consequence on the vulnerability of the urban infrastructure under disruptive events, such as earthquakes or hurricanes, or pandemics, as emerged in the case of Covid-19 (Civljak et al. 2020, WHO 2022). Given the significant number of injured inhabitants needing life-saving treatments during such disruptive events, timely and sustainable access to the local hospital system plays a strategically crucial role, with regard to the public health resilience of the whole urban community, which the hospital system serves. Nevertheless, the functionality of hospital systems themselves have often proven highly susceptible to disruptions, especially, under damaging earthquakes, as the lesson learnt from real-world destructive events around the globe (Yavari et al. 2010, Jacques et al. 2014).

Such observations have triggered several studies aimed to assess the hospital systems' ability to absorb a significant number of casualties following seismic hazards, and provide a viable pathway towards the continuity of their functionalities. For instance, Cimellaro et al. (2011) presents an organizational model for the response of hospital's emergency department, which enables the estimation of the hospital capacity in real-time, considering the impact of the damage of both structural and non-structural components. In their model, as a straightforward indicator of the time-varying functionality of hospitals, the patient's waiting time has been employed to assess its resilience thereof. In light of the wide range of aspects incorporated, from the configuration to the resources, such a model can serve as an adaptive tool for the risk governance with respect to individual hospitals of interest.

More recently, Ceferino et al. (2020) looked into effective response plans of hospital systems under seismic contingencies, and applied their model to Lima city, Peru, under catastrophic earthquake scenarios. Their results demonstrate that the hospital system coordination shall be explored as an effective approach to match demand and supply of the system, and therefore decrease the waiting time of severely-injured patients.

Zhai et al. (2021) proposed a comprehensive framework to model the functionality of earthquake-impacted hospitals, which is set to be measured by the ratio of the number of earthquake-induced patients treated to the total number of patients. To that end, a discrete simulation model, which tracks the treatment process of patients, was developed and incorporated into the framework. Such a framework is applied to a general-purpose, secondary hospital in China, and the outcome reveals that the hospital functionality is highly correlated with earthquake intensity measures and highly impacted by damage to nonstructural components and utilities.

It shall be highlighted that, apart from the functionality of the individual, or networked hospital systems, the prompt and effective post-shock transfer of injured patients plays an at least equally important role, in terms of the minimization of the death toll, and ultimately, the public health resilience of the earthquake-impacted urban communities.

Nonetheless, as repeatedly demonstrated by real-world destructive seismic events, the post-shock transfer of the injured is very likely to be stalled by substantial functionality losses of earthquake-damaged road network embedded in the same urban community (Lin et al. 2010, Hara and Kuwahara 2015). Some studies have been carried out to measure the influence of the functionality losses of road networks, which can be even longstanding, on the post-shock emergency evacuation and transfer (Miller and Baker 2016, Toma-Danila et al. 2022). Moreover, potential panic and irrational reactions of the population are also found to play a uniquely crucial role in successful evacuation and transfer, as highlighted by recent studies on the psychological consequences of hazard events, like earthquakes (Cimellaro et al. 2017, Feng et al. 2020, Wang et al. 2021).

In parallel, thanks to the latest breakthrough in artificial intelligence-capable machines (Kwiatkowski and Lipson 2019, Schrittwieser et al. 2020), connected and autonomous vehicles (CAVs) have been increasingly poised to serve as autonomous transport systems of future urban communities (Lipson and Kurman 2022). Justifiably, large scale deployment and participation of CAVs could also help to revolutionize the post-hazard emergency transfer (Fagnant and Kockelman 2015).

Essentially, under earthquake contingencies, compared to human-driven vehicles (HDVs), CAVs can be particularly competitive, in the sense that:

a. Based on the real-time traffic information, CAVs are capable of planning the travel route autonomously, by resorting to state-of-the-art vehicle-to-infrastructure communication systems (Zhang et al. 2020);
b. CAVs could be strategically helpful, with regard to the transfer of those earthquake-injured inhabitants (Van den Berg and Verhoef 2016), as well as other vulnerable groups (e.g. those disabled, seniors and children inhabitants, who will be unable or struggling to drive on their own).

In view of such a prospect for the amelioration of public health resilience of future urban communities under damaging earthquakes, it is critical to develop a principled understanding on those post-shock transfers with the participation of CAVs, incorporating aspects ranging from the estimation of the casualties and the geographic distribution thereof, to the behavioural pattern of CAVs, and human factors, which has been sparsely studied so far.

To fill in such a knowledge gap, an agent-based model (ABM) is developed in this paper, to simulate the post-shock transfer at city scale, incorporating the participation of CAVs. In this ABM, each earthquake-injured inhabitant in need of hospitalization is modelled as an individual agent, whose behavior is driven by both the hospital choice and the corresponding route planning. The impact of the access to real-time information, and the spatiotemporal evolution of the functionality of the integrated hospital-road system on the decision-making of the agents, are examined in-depth in this study, considering the hybrid deployment of CAVs and HDVs.

To investigate its applicability under catastrophic earthquake scenarios, such an ABM has been employed to model a citywide post-shock emergency transfer across Tangshan city, in Hebei province, China, built on a strike-slip active fault, and the site of a catastrophic earthquake of Mw 7.6 in 1976. The simulation outcome reveals that the availability of information about the real-time functionality of the local hospital system plays a decisive role in minimizing transfer and waiting times. Meanwhile, owing to their capability of intelligent route planning, the substantial participation of CAVs can bolster both the rapidity and effectiveness of post-shock transfer campaigns, in a remarkable way.

The remainder of this paper includes: Section 2, which highlights the ABM framework; Section 3 focuses on the description of the topological configuration of both the hospital and road network embedded in Tangshan city, which serves as the application of the framework. The geographic distribution of the population across the city as well as the location of individual hospitals and their connectivity are also presented; Sections 4 and 5 discuss the simulation outcome and draw the corresponding conclusions, respectively.

2. Agent-based modeling framework of post-shock emergency transfers

Due to the uncertainty of hazard scenarios, the vulnerability of different infrastructure systems and the interaction among them, as well as the political and economic context, the post-shock emergency transfer across modern urban communities is inherently dynamic and stochastic.

As illustrated in Fig. 1, under public emergencies associated with destructive seismic events, significant numbers of injured could be induced by the physical damage and collapse of building structures. Pursuant to the epicenter and magnitude of the earthquake scenario, as well as the location, fragility and occupancy rate of each of those buildings, the level of casualty and the geographic distribution thereof, can be obtained for the whole urban community (Ceferino et al. 2018). For severely-injured inhabitants, it is imperative to transfer them to the closest available hospital to receive life-saving treatments, through either CAVs or HDVs, in an expeditious way. A possible representation of the likely sequence of events relating to injured individuals accessing emergency department facilities can be discretise in the following steps: i) selection of a particular hospital, based on the proximity, the reputation and the real-time information regarding the availability of ward beds (if available) of the local hospital system; ii) thereby selection of a travel route, given the connectivity between that selected hospital and the neighbourhood of departure, as well as the potential connectivity disruption of the road network following the earthquake (Toma-Danila et al. 2022); iii) as the number of injured increases in the immediate aftermath of the mainshock, crowd dynamics will be generated by the collective motion of individual transfers throughout the post-shock phase (Helbing et al. 2000).

Accordingly, the functionality of the hospital system and road network, both of which are essentially serving as the supply capacity regarding the emergency transfer, is affected by the crowd dynamics, leading in turn to the reorientation of the decision-making relating to the selection of hospital destination and travel route, therefore causing the demand to be also temporally and spatially variable and uncertain (Sun et al. 2015). Justifiably, the adaptivity of the route planning of CAVs, who could shun congested road segments pursuant to the real-time traffic flow information, will play a strategic role, to the avoidance of prolonged transfers, which could substantially decrease the mortality rate of earthquake-impacted communities.

To account for the impact of the looped and dynamic interplay between the supply and demand of the integrated hospital system and road network, an ABM framework has been established in this study, as a bottom-up and adaptive computational approach to the post-shock emergency transfers (Ouyang 2014). In this framework, given the earthquake scenario, the quantity and geographic distribution of the casualty is assessed in the absorption phase (Ouyang et al. 2012), while the mass transfer is modelled in the corresponding phase of the immediate aftermath of earthquakes, where each of the vehicle (either CAVs or HDVs) participating in the transfer will be modelled as an intelligent agent (Sun et al. 2021). The trajectory of the emergency transfer throughout the whole seismic event can be thereby tracked, the rapidity and effectiveness of which will serve as a measure on the public health resilience of the whole community.

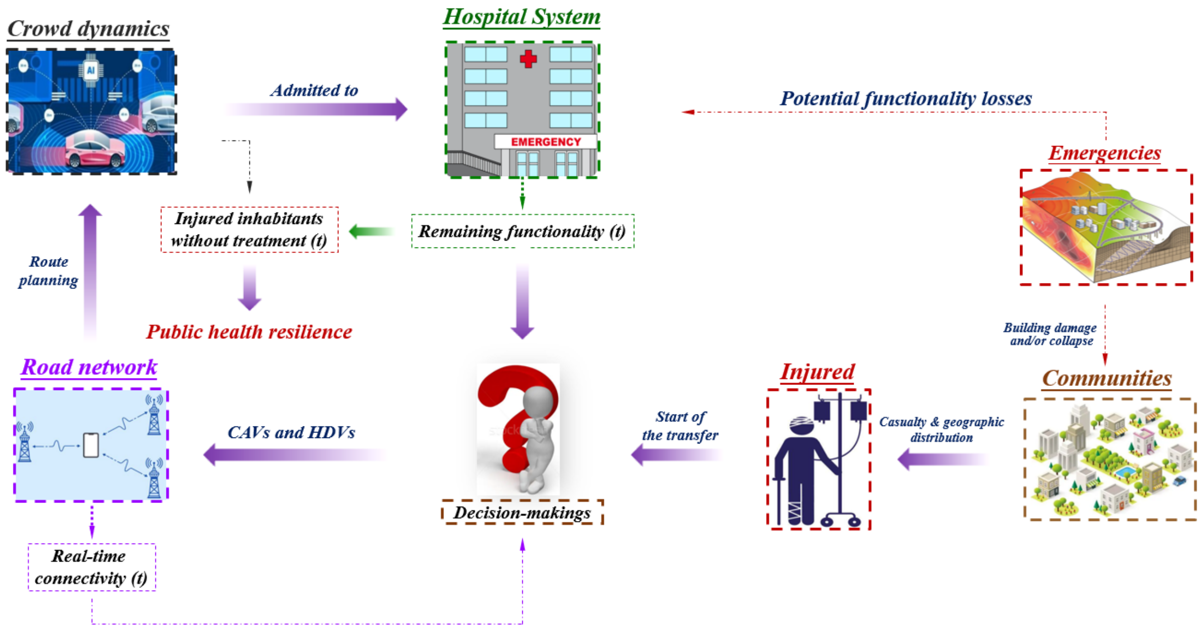


Fig. 1. Post-shock emergency transfer across the earthquake-impacted community-hospital system-road network.

2.1. Earthquake hazard and casualty model

In this framework, to assess the number and distribution of the earthquake-injured inhabitants, damage behaviour of each of building structures across the whole urban community is modelled by its fragility and the corresponding intensity measures, which are usually determined by ground motion attenuation models and the given earthquake scenario (Stupazzini et al. 2021). In this study, without loss of generality, the attenuation model developed by Atkinson and Boore (1995), applicable to earthquakes with $4 \leq M_W \leq 7.25$, is incorporated into the framework, to enable the study of post-shock emergency transfer under earthquake scenarios with high magnitude, whereby trivial simulation outcomes can be avoided.

Mathematically, the peak ground acceleration, which is the intensity measure employed in this study, is therefore obtained following Eq. (1):

$$\log(PGA) = a_1 + a_2(M_W - 6) + a_3(M_W - 6)^2 - \log R_e - a_4 R_e \tag{1}$$

Here, M_w and R_e refers to the earthquake magnitude and the corresponding epicentral distance, respectively; Meanwhile, the value of the parameters a_1, a_2, a_3 and a_4 are set to be 3.79, 0.298, -0.0536 and 0.00135, respectively, as obtained from regression analysis (Atkinson and Boore 1995). Alternative attenuation laws specific to the site of interest or intensity measures, suitable to identify the response of specific structural typologies, can be equally employed in the framework.

A thorough review of casualty estimation methods has been provided recently by Yan et al (2021). Models can be empirical (based on past data) or predictive (based on causal factors, such as buildings' vulnerability) and be applicable at different scales, from regional to local. In the present study, given the damage state of each individual building determined through fragility analysis based on the peak ground acceleration at its site, the community-level casualty analysis can be run following the model proposed by Coburn et al. (1992), which accounts for the occupancy rate of buildings and the total population of the community. It is noteworthy that, in this study, only those inhabitants sustaining the hospitalization-level injury are assumed to participate in the post-shock emergency transfer, whereby the city-wide simulation can be more tractable.

Besides, in view of the spatial-temporal variability of the population across modern urban communities driven by their modus operandi, the impact of different timing of earthquake hazards on the post-shock transfer is also considered in this study (Ceferino et al. 2020). Specifically, a daytime and a nighttime scenario, respectively, will be considered. They are simulated by considering that the majority of the inhabitants are located in the downtown area of the community of interest, during daytime, while during nighttime the majority will be in residential neighborhoods, which are often located at the periphery of modern communities.

2.2. Hospital selection criteria

Let $C = \{n_1, n_2, \ldots, n_m\}$ denote the array of neighborhoods embedded in the urban community of interest, where m is the total number of those neighborhoods. Meanwhile, $HS = \{h_1, h_2, \ldots, h_k\}$ stands for the local hospital system consisting of k individual hospitals. In this research, for hospital h_i ($i \in k$) in the *HS*, its functionality will be characterized by two attributes, denoted as C_i^{max}, and $IA_i(t)$, respectively. As a constant, C_i^{max} stands for the maximum healthcare capacity of h_i, while $IA_i(t)$ refers to the number of the injured, who have already been admitted to this hospital, at time point t. Its remaining healthcare capacity at such a moment, denoted as $RC_i(t)$, can be therefore obtained following Eq. (2):

$$RC_i(t) = \begin{cases} C_i^{max} - IA_i(t), & IA_i(t) < C_i^{max} \\ 0, & IA_i(t) = C_i^{max} \end{cases} \tag{2}$$

Equation 2 shows that any injured patient arriving at h_i at a time t^+ greater than time $t=T_0$, when $RC_i(T_0)=0$, will need to re-select among the remaining hospitals with spare capacity to receive medical treatments. By doing so, the heterogeneity (e.g. regarding the functionality) of modern hospital systems can be taken into account, by the proposed ABM framework. This condition arises from the assumption, legitimate in the timeframe of this simulation, that no patient will be discharged during the period of time needed to deliver all casualties to an emergency department unit.

In the pre-shock phase, apart from those centralized transfer strategies (Ceferino et al. 2020), the hospital selection of individual inhabitants will be collectively driven by a host of influential factors, ranging from the reputation of every single hospital, to the personal preference and household financial conditions (Hassan and Mahmoud 2020), and is thus fairly complex unregulated phenomenon. In the immediate aftermath of an earthquake, however, given the type of injuries usually sustained, the travel time needed to reach a given hospital, also plays a decisive role in the selection of the destination (Del Papa et al. 2019). Clearly, the shorter the travel time is, the more likely those severely-injured can access life-saving treatments, and thereby survive.

As an endeavor to balance the trade-off between the inclusiveness and computational tractability, the hospital selection of injured inhabitants in neighborhood n_j ($j \in m$) will be following the criterion formulated in Eq. (3):

$$P_{i,j} = \frac{RC_i(t)^{\varpi} D_{i,j}{}^{-\xi}}{\sum_{i=1}^{k} RC_i(t)^{\varpi} D_{i,j}{}^{-\xi}} \tag{3}$$

whereby, $D_{i,j}$ stands for the length of the shortest path between that neighborhood and hospital h_i, which is obtained using the classical Dijkstra algorithm (Dijkstra 1959). The attraction coefficient, denoted as ϖ, is introduced to serve as a measure on how decisive the remaining healthcare capacity of one particular hospital is, with regard to the selection of the destination: the higher the ϖ value, the more likely hospitals with greater remaining capacity are chosen. Similarly, the resistance coefficient, denoted as ξ, is employed to measure the effect of the travel distance on destination decision-making. Mathematically, for each hospital, their distance to the neighborhood of interest will be increasingly disproportionate to the likelihood of being picked by the inhabitants living there, in the case of higher ξ values (Wu et al. 2010).

It is noteworthy that, in this study, it is also assumed that the decision-making of the injured inhabitants, who are modelled as the autonomous agents in the ABM framework, will be independent from others. Besides, to avoid unaffordable computational costs, throughout the post-shock emergency transfer, once the decision is made, the re-selection of the targeted hospital en route will not be considered in the following case-study, until the arrival at the selected one (Wang et al. 2016). If, upon arrival, the selected hospital capacity is saturated, they will then need to re-select their new destination, according to Eq. (3).

Furthermore, it shall be highlighted that, the hospital selection following Eq. (3) is conditioned upon the enduring information sharing, which may not hold true, with respect to damaging earthquakes. Regarding those cases, the agents will select the hospital based upon the pre-shock functionality level, namely, replace $RC_i(t)$ with C_i^{max}, in Eq. (3).

2.3. Travel route planning of CAVs

Inhabitants engaging in post-hazard evacuations and transfers would often resort to various ways of travel (Li et al. 2020). Nonetheless, given the urgency of the rescue in the wake of damaging earthquakes, all the injured inhabitants participating in the post-shock transfer are assumed to be transferred to the local hospital system by vehicles (not by walking), in this study. Without losses of generality, it is assumed that agents driving HDVs are experience-based, who will always choose the shortest path to the targeted hospital, as obtained through the topology of the local road network, regardless of the real-time traffic flow en route. By comparison, CAVs are assumed to be able to reorient their path through dynamic planning, in the course of post-shock transfers.

Mathematically, dynamic planning is a general paradigm, which can be employed to fulfil the optimization objective, with respect to sequential decision-makings (Russell and Norvig 2021). Regarding CAVs participating in post-shock transfers, the objective is the minimization of the expected travel time (ETT). Pursuant to that objective, as shown in Fig. 2, for a CAV agent (who is departing from the neighborhood n_j and has picked the hospital h_i) at the l^{th} decision-moment (referred to as DM_l) en route, i.e. the l^{th} crossroad it has arrived at, the action to be taken (namely, which particular road segment it will then switch to), denoted as A_l, is determined by Eq. (4):

$$A_l = \underset{p}{\arg\min}\ ETT\big(TR(V,A), TF(DM_l), a_p\big) \quad (p=1, 2, \ldots, Q) \tag{4}$$

Here, $TR(V, A)$ is the topological model of the local road network established based on graph theory, where $V = \{v_1, v_2, \ldots, v_R\}$ is the set of R vertices of the network, which stand for the crossroads, neighborhoods and hospitals, respectively. Meanwhile, $A = \{a_1, a_2, \ldots, a_T\}$ refers to the corresponding T arcs, namely, the road segments. Among those arcs, $a_p\ (p=1, 2, \ldots, Q)$ stand for the array of those Q arcs connected to the l^{th} crossroad where the agent is now, excluding the one, which the agent has just travelled along (whereby infinite loops can be avoided). In particular, to consider the impact of the real-time traffic flow across the whole road network, referred to as $TF(DM_l)$, on the adaptive decision-makings of CAV agents, the classic impedance function has been introduced into this framework (Branston 1976), and the ETT needed regarding road segment a_p (denoted as $ET_p(DM_l))$ is therefore obtained by Eq. (5):

$$ET_p(DM_l)) = FT_p\left(1+\alpha\left[\frac{TF_p(DM_l)}{MT_p}\right]^{\beta}\right) \tag{5}$$

Here, FT_p denotes the free travel time of a_p that can be determined by L_a/v_c, where L_a stands for the length of this arc, while v_c refers to the free flow travel speed of the CAV. Meanwhile, $TF_p(DM_l)$ and MT_p denote the real-time traffic flow of a_p at the moment DM_l, and the maximum traffic-carrying capacity of such a road segment, respectively. Moreover, the values of the parameters α and β have been set to be 4.5 and 4.0, respectively, in this research (Feng et al. 2020).

As shown in Fig. 2, driven by the dynamic programming and the choice of a_p, the CAV agent will virtually reach the next crossroad v_l^p, after a period of time $ET_p(DM_l))$. To minimize the total expected travel time of the transfer, the agent can, at this point, choose a route (among all the possible ones, pursuant to the choice of a_p) associated with the minimum travel time needed thereafter to arrive at the hospital h_i from v_l^p (Hart et al. 1968). For any particular route R_g ($g = 1, 2, \ldots, NR_l^p$), the corresponding time span, denoted as $TT(R_g)$, can be thereby determined through *Eq. (6)*:

$$TT(R_g) = \sum_{s=1}^{N_p^g} FT_s\left(1+\alpha\left[\frac{RT_s(DM_l)}{MT_s}\right]^{\beta}\right) \tag{6}$$

Here, N_p^g stands for the total number of road segments that route comprises. Therefore, $ETT\big(TR(V,A), TF(DM_l), a_p\big)$ can be obtained by Eq. (7):

$$ETT\big(TR(V,A), TF(DM_l), a_p\big) = ET_p(DM_l)) + \min(TT(R_g)), g = 1, 2, \ldots, NR_l^p \tag{7}$$

As illustrated in Fig. 2, after the execution of the action A_l, the CAV agent will travel along the corresponding road segment, until the arrival of the next crossroad, namely, the $(l+1)^{th}$ one. The decision at such a moment, DM_{l+1}, will be made following the same dynamic programming procedure described above. Such an iteration will continue, until the agent has reached hospital h_i eventually.

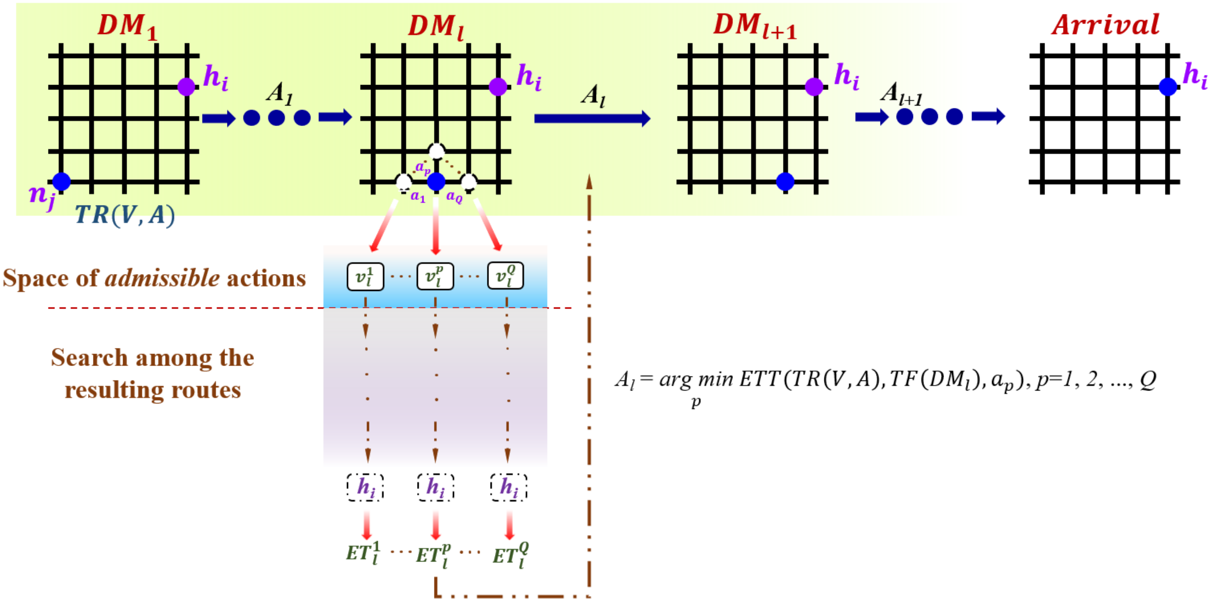


Fig. 2. Dynamic route planning of CAV agents.

2.4. Traffic dynamic model on the system-level

Despite the straightforward pattern of the individual agent's behavior presented above, it can be fairly challenging to model the dynamic, self-organized traffic flow across city-scale road networks (Helbing and Mazloumian 2009) on the system-level, when compounded by earthquake post-shock damage, in view of the potentially prolonged traffic congestion, as well as the panic and irrationality of considerable quantity of individual drivers (Feng et al. 2020). To ensure the tractability of the simulation, a queuing model (Cetin et al. 2003) has been integrated into the ABM framework, whereby the traffic dynamics regarding the mass crowd consisting of both CAVs and HDVs can be shaped. Following such a model, when an agent who is driving either a CAV or HDV has reached a crossroad, it can switch to the next road segment, only if the following requirements have all been fulfilled:

(1) Given a set flow limit for each road segment, the number of vehicles that can switch at every time step cannot exceed that limit;

(2) The remaining space of the targeted road segment can still allow for additional vehicles;

(3) In case of multiple vehicles being ready to switch at the same time, the one which has reached the crossroad first will also be allowed to go first.

2.5. Performance of post-shock emergency transfers

To gauge their performance at system-level, the gross transfer time (GTT) has been proposed as the measure on the city-scale transfers, and can be quantified by Eq. (8):

$$GTT = \sum_{v=1}^{N_w} DT_v \tag{8}$$

where N_w is the total number of injured people, who are engaging in the post-shock transfer, under any particular earthquake scenario. Meanwhile, DT_v denotes the total travel time from its origin to the hospital of the agent v. Besides, it is also noteworthy that, in this framework, such a duration does not include the hospital services' waiting time, upon arrival. Additionally, once admitted to, the discharge of those injured inhabitants from hospitals will not be modelled neither in this study, given the time scale of the immediate aftermath of hazard events.

3. Case study

3.1. Topology and operational conditions of the hospital system-road network

To examine its applicability, the ABM framework developed in Section 2 has been applied to the integrated hospital system-road network of Tangshan city, which is an industrial hub located in one of the most earthquake-prone regions of China (He et al. 2016), and a corresponding case study was conducted under hypothetical, damaging earthquake scenarios. The simplified topology of such a networked hospital system-road network-community is plotted in Fig. 3. For each of the neighborhood across the whole network, without losses of generality, it is assumed that the reinforced concrete and masonry structures will account for 50% of the gross number of buildings, respectively. Besides, the fragility model proposed by Jaiswal et al. (2011) is employed to shape the seismic response of these two different types of structures.

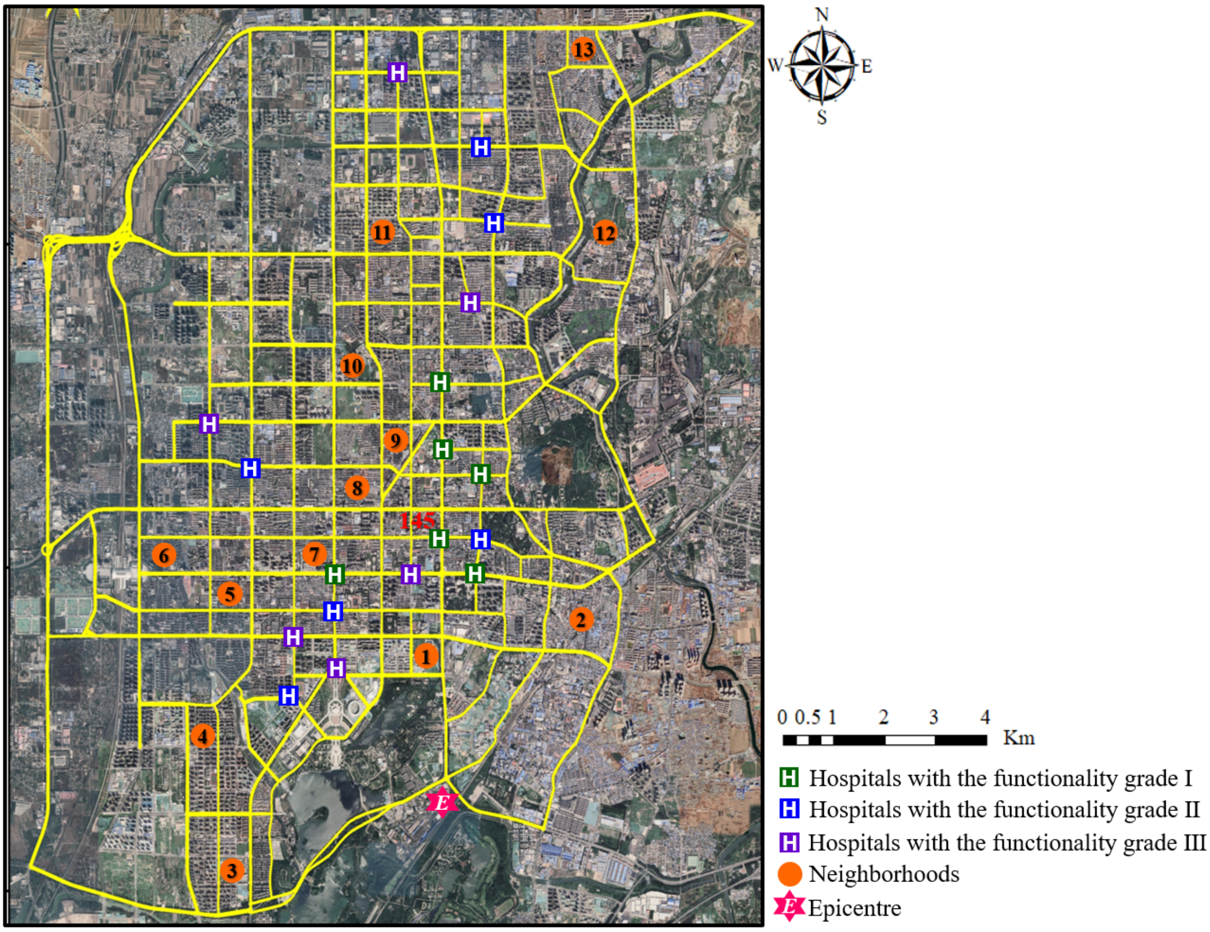


Fig. 3. Topology of the integrated hospital system-road network-community.

Specifically, the road network consists of 216 vertices and 375 arcs. Meanwhile, 18 hospitals with different functionality grades have been incorporated into the hospital system. As shown in Table 1, a total of three functionality grades, measured by the quantity of ward beds, are considered in this study (Li et al. 2008). Besides, each of those grades has been assigned to 6 hospitals, so that the total number of beds coincides with the number of injured (see Table 1 and Fig. 3).

Table 1. Information of the hospital system

Functionality grades	Corresponding nodes						Number of ward beds
I	94	117	130	145	155	159	2,400
II	32	57	112	146	168	203	1,200
III	13	76	99	157	180	193	680
Total							25,680

In parallel, the corresponding urban community includes 13 neighborhoods, whose population is summarized in Table 2, leading to a total of 702,394 inhabitants residing in the whole area. For each of those neighborhoods, its population are assumed to be equally distributed on those nodes associated with it.

Table 2. Information of the neighborhoods of the community

Number	Neighborhood	Corresponding nodes						Population
1	Guang Chang	1	184	195	196			42,771
2	Yong Hong Qiao	1	161	186	187			21,743
3	Liang Jia Tun	2	208	213	214			62,691
4	Hui Min Dao	1	190	199	200			70,391
5	You Yi	1	153	165	166			41,486
6	Guo Yuan Zhen	1	122	138	139			64,715
7	Da Li	1	125	141	142			66,001
8	Xiang Yun Dao	1	126	127				14,460
9	Wen Hua Lu	1	104	116				66,677
10	Ji Chang Lu	8	83	92	93			68,201
11	Gao Xin Qu	4	41	54	55	59	60	100,002
12	Long Dong	4	46	63	72	73		44,426
13	He Bei Lu	7	8	16	17			38,830

3.2. Scenario-based simulation following the ABM framework

In view of the significant uncertainty associated with seismic hazards, the behavioral pattern (regarding the hospital selection, as well as the route planning) of individual injured inhabitants, as well as the number of available CAVs, following the ABM framework described above, Monte Carlo simulations are run to consider their collective impact on the city-scale, post-shock transfers. For both the CAV and HDV, their travelling speed are set to be 4m/s in this study, to consider the potential influence of debris, etc., throughout seismic events.

Meanwhile, given the expensive computational cost, 50 Monte Carlo simulations are run for each single scenario included in this case study, which have been listed in Table 3.

Table 3. Setup of scenarios included in the case-study

Scenario	Information accessibility of each single hospital	Timing of earthquakes
1	yes	daytime
2	no	daytime
3	yes	nighttime
4	no	nighttime

Specifically, in light of the modus operandi of most modern urban communities, the majority of their inhabitants are expected to be either working, studying, or shopping across downtown areas, in the daytime. Conversely, they are supposed to be resting or sleeping at home, usually located on the outskirts of the city, at nighttime. Therefore, the timing of the mainshock of destructive earthquakes is expected to have a nonnegligible impact on the post-shock transfer, given that distinct spatial distribution of populations. Accordingly, two different scenarios, where earthquake is occurring at daytime and nighttime, respectively, have been considered in this research. In the first case, 80% of the population affiliated to neighborhoods with ID Nos. 2, 3, 4, 11, 12, and 13 are assumed to relocate to neighborhoods with ID Nos. 1, 5, 6, 7, 8, 9, and 10 (Fig. 3). On the contrary, in terms of nighttime, the converse applies. The distribution of the injured population for the two cases is detailed in Table 4.

Table 4. Distribution of injured inhabitants under the scenario with earthquake at daytime and nighttime

Number	Neighborhood	Daytime	Nighttime
1	Guang Chang	3,071	437
2	Yong Hong Qiao	223	2,857
3	Liang Jia Tun	545	3,971
4	Hui Min Dao	551	4,487
5	You Yi	3,738	312
6	Guo Yuan Zhen	4,369	433
7	Da Li	4,157	514
8	Xiang Yun Dao	1,715	115
9	Wen Hua Lu	3,132	497
10	Ji Chang Lu	3,134	467

11	Gao Xin Qu	585	5,283
12	Long Dong	269	3,932
13	He Bei Lu	191	2,375

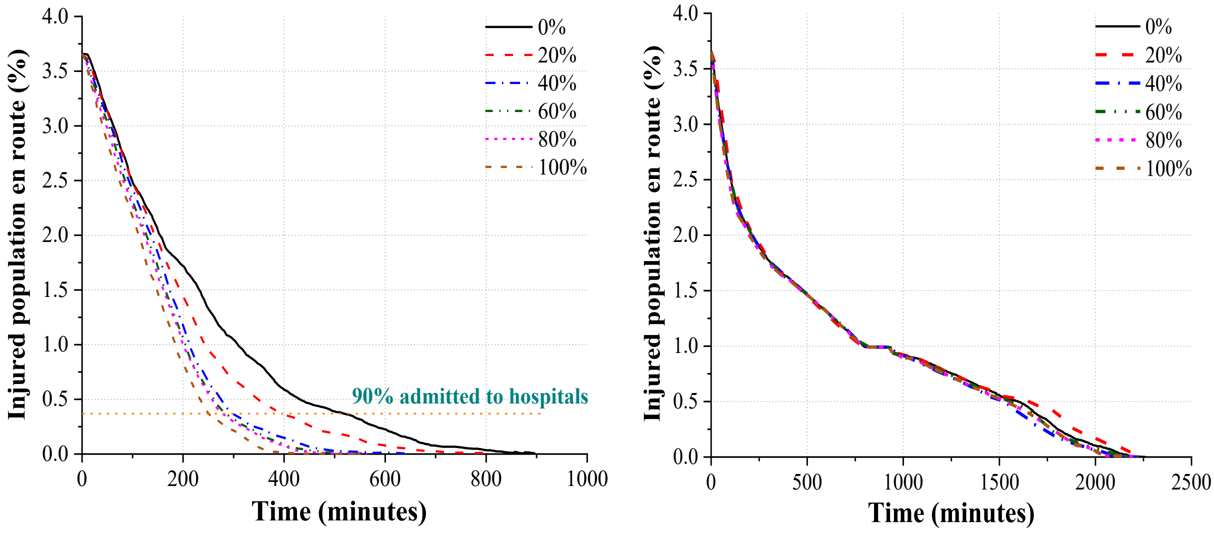
It is also noteworthy that, real-world earthquake events have demonstrated that modern telecommunication systems can also be seismically-vulnerable, and thus sustain earthquake-initiated functionality losses (Krishnamurthy et al. 2016), whereby the information sharing regarding the real-time functionality status of the local hospital system can be substantially disrupted, throughout post-shock emergency transfers. Therefore, for each of the two scenarios described above, the cases where the real-time information is, and is not available, respectively, will be further introduced. Hence, a total of four different scenarios have been generated for this case study, as shown in Table 3. Moreover, for each of those scenarios, different proportions of CAVs participating in the post-shock emergency transfer are accounted for by considering five cases, from 20% to 100% in increments of 20%.

Finally, to generate nontrivial and realistic simulation outcome, one particular earthquake scenario with the magnitude of 7.25 and epicentral depth of 10 km are considered in this paper, which is consistent with the real-world, historical seismic activities recorded across Tangshan city (Lomnitz and Lomnitz 1978, Chen et al. 2021).

4. Simulation results

4.1. Daytime Scenario

Figure 4 tracks the median percentage of the injured population en route (IPER) to hospitals versus the gross population in the region, throughout the post-shock emergency transfer, under the daytime scenario. In particular, the results associated with the corresponding cases with and without the real-time information sharing, regarding the functionality status of the local hospital system (which is measured by the amount of the remaining ward beds, as described in Section 2) have been plotted in Figs. 4(a) and 4(b), respectively.



(a) With information sharing (b) Without information sharing

Fig. 4. Median percentage of injured population en route under daytime scenario.

As shown in Fig. 4, the number of injured in need of hospitalization is found to reach 25,680, which account for 3.656% of the total population, under such a catastrophic earthquake scenario. From Fig. 4(a), notably, the post-shock emergency transfer is demonstrated to be going more smoothly and promptly, when more CAVs are engaged in the campaign. Quantitively, in terms of the two extreme cases (with 0 and 100% CAVs, respectively), the corresponding GTT (obtained following Eq. (8)) of the whole transfer campaign are found to be approximately 15 and 9.1 hours, respectively, signaling a 39% reduction, owing to the presence of CAVs. In particular, it can be further found from the trajectory associated with the case with 100% CAVs that, the IPER value is decreasing with an almost-constant slope until the 250^{th} minutes after the shock, when 90% of the injured have been delivered to hospitals. By comparison, in the case without any CAV, its trajectory reveals that the transfer is becoming slower after 50% of the injured are delivered to the local hospital system, and it takes 520 minutes, that is 2.08 times longer (than that associated with the case with 100% CAVs), for the 90% to be transferred. Justifiably, such a significant reduction of GTT is strategically crucial to the minimization of the fatality rate, as well as socio-economic losses of earthquake-impacted urban communities.

Table 5. Median GTT with regard to different percentage of CAV agents under daytime scenario

Scenarios considered	GTT (minutes)					
	0%	20%	40%	60%	80%	100%
scenario 1 (with)	900	805	641	561	567	547
scenario 2 (without)	2,261	2,247	2,217	2,224	2,208	2,191

Nonetheless, it shall be also highlighted that the resulting GTT is not decreasing linearly with the growing percentage of CAVs participating in the transfer campaigns. From Fig. 4(a), shows a step change in the delivery when the proportion of CAVs reach 40%. As shown in Table 5, the resulting GTT in such a case is 10.7 hours, 28.7% shorter than that regarding the baseline. On the other hand, the time reduction for higher proportions of CAVs is not really significant. Such an observation suggests that, given their autonomous decision-making capabilities under public emergencies, the deployment of a fleet of CAVs, even just on a moderate scale, can be leveraged as an effective tool to ameliorate public health resilience of future urban communities imperiled by natural hazards.

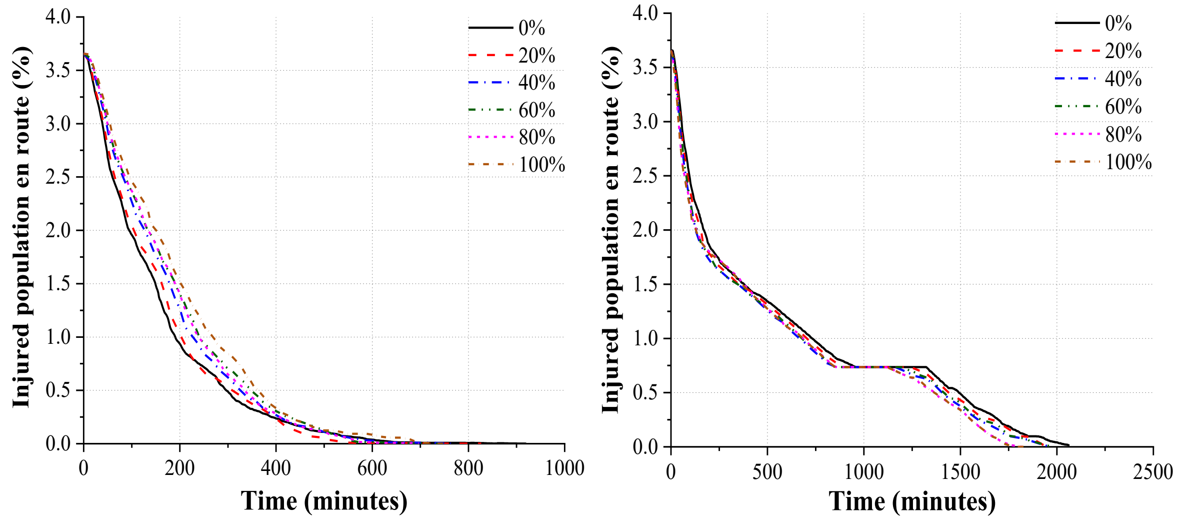
Moreover, the contribution of CAVs to public health resilience appear significantly diminished, when the real-time information regarding hospital system functionality is inaccessible, as shown in Fig. 4(b). Although the slope is initially steeper than the case with information, the baseline GTT is more than doubled. Overall, the trajectories associated with all the different cases are overlapping, throughout the entirety of the post-shock transfer. Quantitatively, even for the case of 100% CAVs, the resulting GTT reaches 36.5 hours, merely 3.1% lower than that of the baseline, signaling an almost-negligible contribution of CAVs on the post-shock transfer. Such a stark contrast between scenarios 1 and 2 reveals that the contribution of CAVs can be maximized, only when real-time information about the hospital capacity is continually available. Hence, it further suggests that the interdependence among different critical infrastructure systems should be accounted for, in terms of the risk governance and public health resilience amelioration of future urban communities.

In parallel, as shown in Table 5, it can be found that, regarding the cases with 0% and 100% CAVs, for scenario 2, the obtained GTT is 2.5 and 4 time longer than the corresponding values associated with scenario 1, respectively. It therefore reveals that, due to the lack of real-time information, substantially more injured inhabitants will be delivered to hospitals with initially higher functionality grade, which can be thus overwhelmed, given such a significant healthcare demand, in the wake of damaging earthquakes. As a result, considerable fraction of those wounded will then need to re-select, leading to a much longer transfer campaign. This is identified in Fig. 4(b) by the portion of the GTT curve with horizontal tangent.

4.2. Nighttime Scenario

For the nighttime scenarios, a larger proportion of the injured are distributed across neighborhoods with the ID Nos. 2, 3, 4, 11, 12, and 13, whereas most of the hospitals are located across the downtown area (Fig. 3). The corresponding post-shock transfer is thus expected to be more time-consuming, given the longer distance to the local hospital system, and likely to be hindered by the limited choice of alternative routes to the hospital and therefore the possibility of hold ups for many of the injured.

As shown in Table 6, unlike the earthquake at daytime, for both scenarios 3 and 4, the resulting GTTs are not found to be decreasing monotonically, given the increasing percentage of CAVs. Specifically, the GTT reaches the minimum, when the percentage of CAVs is set to be 80% for both scenarios, leading to a reduction by 24.2% (11.6 hours versus 15.3 hours) and 11.7% (30.4 hours versus 34.4 hours), respectively, highlighting again that the lack of information sharing will reduce the effect of CAVs.



(a) With information sharing (b) Without information sharing

Fig. 5. Median percentage of injured population en route under nighttime scenario.

In particular, Fig. 5(a) reveals that, without the participation of any CAV, the IPER reduces more quickly in the earlier stage, compared to other cases. Such a significant difference from the results shown in Fig. 4(a) shows that, as the simulation starts with the road network without any traffic flow, the transfer is initially more efficient when the injured choose the shortest path, rather than the input provided by dynamic route programming. However, the transfer becomes increasingly slow in the latter stage, when a relatively small proportion of agents are engaging in the re-direction and new destination as the treatment in the targeted hospital is inaccessible on arrival, and they are required to travel among different hospitals, across the crowded downtown area. Nevertheless, owing to their adaptivity, all the other cases with CVAs catch up and outpace the baseline, even though both the reduction in time and the percentage of injured involved are rather marginal.

The impact of the hospital re-selection is more clearly pronounced, for the post-shock transfer under scenario 4, as shown in Fig. 5(b). It can be found that, until 80% of the injured have reached the local hospital system, the trajectories associated with all the different cases are nearly identical, suggesting a fairly marginal contribution of the increasing amount of CAVs, which is similar to the pattern found from Fig. 4(b).

Table 6. Median GTT with regard to different percentage of CAV agents under nighttime scenario

Scenarios considered	GTT (minutes)					
	0%	20%	40%	60%	80%	100%
scenario 3 (with)	919	828	765	759	697	756
scenario 4 (without)	2,066	1,948	1,949	1,966	1,824	1,836

However, regarding the baseline case, a long plateau is observed thereafter, indicating that a significant fraction of the injured population, who are travelling along the shortest path to the re-selected hospital, without exploring the connectivity of the other road segments of the road network, are stuck in traffic jam. By comparison, as more CAVs are deployed, the length of the plateau shortens, although the slope remains similar among the different cases.

4.3. Discussions

In Sections 4.1 and 4.2, the obtained simulation outcome regarding the 4 different scenarios have highlighted the complexity of the post-shock transfer of large number of injured inhabitants across modern urban communities, as a combined result of different earthquake scenarios, the functionality supply capacity of the local hospital system, the topological configuration of the corresponding road network, as well as the crowd dynamics collectively driven by the behavioral pattern of each individual agents engaging in the transfer campaign. Against this backdrop, this Section attempts to dig further into the result, and generate new insights that can be generalizable to other urban communities with different scales and infrastructures systems with different functionality capacities and topologies.

Quantitatively, among all the cases considered in Sections 4.1 and 4.2, the one with 100% CAVs under scenario 1 has been found to lead to the minimum GTT of the whole transfer campaign, although similar results can be obtained by engaging only 60% of CAVs. As described above, according to the setup of such a case, most of the injured inhabitants will be in the downtown area, where a concentrated functionality demand on the hospital system has been thus generated. Meanwhile, it can be found from Fig. 3 that, all those hospitals with the functionality grade *I* are also embedded in such an area (which is indeed fairly common, with regard to the configuration of the majority of modern urban communities), leading to a better match between the local functionality supply and demand, whereby the re-selection and re-transfer can be largely avoided. In addition, it shall be highlighted that the redundancy of the local road network topology is indeed playing an equally decisive role to the effective transfer, in the sense that all the hospitals in such an area are well-connected, and thereby much more accessible from different neighborhoods nearby, especially, when considerable number of CVAs, which benefit from the real-time connectivity of the whole road network, are participating in the transfer. For example, as shown in Fig. 3, the hospital at node 145 is not only close to all those neighborhoods with ID Nos. 1, 5, 6, 7, 8, 9, and 10, but is also reachable by up to a total of four different road segments. By comparison, the hospital system is considerably sparser in the peripheral neighborhoods. In addition, the topology of the road network in those areas is also significantly less redundant, which indicates that hospitals can be also less accessible in such areas (Byun and D'Ayala 2022). As a result, traffic congestion is thus more likely to be triggered in the course of the emergency transfer, especially, when all the agents choose to travel by adhering to the shortest path to those hospitals they have picked, which will then delay the whole campaign. However, regarding scenario 1, where earthquakes occur at daytime, limited number of injured inhabitants will be located at periphery areas of the community, leading to a lower demand on the network, which helps to maintain a local equilibrium. In particular, when more CAVs have been engaging in the campaign, the stagnancy associated with the post-shock transfer has been effectively alleviated, throughout both the downtown and periphery areas. As shown in Fig. 4 (a), no delay is observed until the moment when the majority of the injured inhabitants have been admitted to the hospital system already.

However, as shown in Section 4.2, the advantage of CAVs can be substantially reduced, in the case with the majority of the injured in the periphery, which is the setup of scenario 3. The mismatch between the supply and demand in such a scenario, with regard to the hospital system, will lead to longer-distance travel for many injured inhabitants, who need to reach those hospitals in the downtown. In particular, due to the sparsity of road segments in the periphery and the limited river crossing, the dynamic route programming of CAVs would sometimes bring about the detour (to circumvent those congested segments), which will, paradoxically, prolong the transfer. As shown in Fig. 5 (a), despite the shorter GTTs regarding the whole campaign, those cases with the presences of CAVs are even trailing the baseline, in the early stage of the transfer.

Compared to scenarios 1 and 3*,* transfer in scenarios 2 and 4 are significantly more sluggish, leading to GTTs that are up to 4 times longer. As mentioned above, the uninformed choice of hospitals will cause re-selection and re-transfer for a large number of agents, as a result of the absence of the real-time information sharing in such two scenarios. When it comes to the real-world hazard events, the significant re-transfer endeavor would contribute to the lack of coordination of the traffic flow across local road networks, alongside other vehicles (e.g. driven by those who are not wounded by the hazard, but are moving to other intact communities), which are not even modelled in this framework. It shall be particularly highlighted that, such an uncoordinated traffic flow will have a cascading effect on the post-shock transfer, in the sense that the long-lasting and pervasive congestion on several road segments (especially those critical ones, for example, connecting those hospitals with functionality grade *I*) will limit the contribution of CVAs, despite their route planning capabilities (as shown in both Figs. 4 and 5), and ultimately, increase the mortality and socio-economic losses under hazard events. Furthermore, the other emergency responses endeavors (e.g. fire extinguishment, debris removal, and etc.) will also be substantially hindered, and the resilience of the whole community will be thus reduced.

In summary, the agent-based model developed in this research has highlighted that uncoordinated transfer on the system-level can be triggered by the lack of adaptivity on the individual level. On the contrary, more rational decision regarding the hospital selection, owing to the access to the real-time information of the local hospital system, can significantly streamline the citywide transfer throughout public emergencies. Furthermore, behavior of those transfers can be further ameliorated through the deployment of the fleet of CAVs, who are essentially able to maximize the usage of the real-time connectivity of the local road network, through dynamic route planning. Therefore, in view of its granularity, the proposed framework can serve as a viable tool for stakeholders and administrators of future urban communities to develop appropriate emergency response strategies, while formulating risk governance policies. Besides, given its inclusiveness, more complex behavior patterns of individuals and other sociological factors can be also incorporated into such an ABM framework.

Notwithstanding the new insights generated and discussed above, it should be noted that, given the burgeoning study into the self-driving vehicles (Badue et al. 2021), more research needs to be conducted to model the nuanced responsive behavior of future CAVs under complex on-road conditions, throughout public emergencies, whereby the developed framework in this paper can be further tailored to future urban communities with intelligent road networks (Fu et al. 2021).

5. Conclusions

Throughout the past decades, urbanization has become an inexorable trend around the globe. Accordingly, modern urban communities have served as the engine for wealth creation and technological advance, in most of the nations (Bettencourt et al. 2017). Nevertheless, the advantage of booming urban communities has often been found to be offset by the recurrent curses of various catastrophes (Glaeser 2011), especially, natural hazards. Against this backdrop, the public health resilience of those hazard-impacted urban communities can be thus jeopardized, and it is thus strategically crucial to develop a principled understanding on the post-hazard massive transfer across those communities, incorporating aspects ranging from hazard scenarios, to the behavioral pattern of injured inhabitants, as well as the topological configuration and operational dynamic of an array of critical infrastructure systems serving them, throughout public emergencies.

Meanwhile, in light of the increasing penetration of artificial intelligence that is revolutionizing the modus operandi of modern urban communities, deployment and participation of CAVs are also expected to reshape those massive transfer campaigns. Compared to conventional vehicles, i.e. HDVs, CAVs are capable of planning the travel route autonomously, by exploring the real-time functionality status of local road network in the course of the transfer, which can be strategically crucial to the coordination among individual vehicles engaging in those campaigns. Moreover, CAVs could also be particularly conducive to the transfer of those hazard-injured inhabitants, as well as other vulnerable groups, who are struggling to drive on their own. Nevertheless, research on the impact of the participation of CAVs on large-scale, post-shock transfer has been merger, so far.

To fill in such a knowledge gap, as a bottom-up approach to complex and large-scale socio-economic systems with interacting entities (Batty 2007, Sun et al. 2019), an ABM framework, where each injured inhabitant is modeled as an independent agent, who can be transferred to local hospitals by either HDVs or CVAs, has been developed in this study. To demonstrate its applicability, this framework is applied to model the post-earthquake emergency transfer across the networked hospital system-road network-community in Tangshan city, which is located in one of the most earthquake-prone regions of China. Particularly, in such a case-study, the impact of the initial spatiotemporal distribution of earthquake-initiated wounded inhabitants, the percentage of inhabitants (engaging in the transfer campaign) transferred by CAVs, and the real-time information of the functionality status of the local hospital system on the citywide transfer, has been investigated. A host of conclusions have been drawn from the outcome of that study, as the following:

1. Owing to its granularity, the ABM framework proposed in this paper can deliver a nuanced modelling on the city-scale transfer campaigns, with the participation of a fleet of CAVs;
2. The spatial distribution of earthquake-initiated wounded inhabitants is found to have a profound impact on the behavior of the post-shock transfer. Regarding scenarios with earthquake at nighttime, the mismatch between the supply and demand on the hospital functionality will render the transfer campaign susceptible to disruptions;
3. The lack of real-time information regarding the hospital system functionality will substantially complicate and prolong post-shock transfer campaigns, in view of the system-level incoordination, as a result of the irrational hospital selection of a significant fraction of injured inhabitants;
4. The participation of large number of CAVs can significantly expedite the post-shock transfer. In terms of earthquakes at daytime, a reduction of nearly 30% has been observed, regarding the gross transfer time in the case of just 40% of CAVs. It can be thereby concluded that the deployment of a fleet of CAVs, even with only a moderate size, can be strategically critical to the minimization of mortality of earthquake-impacted urban communities. It is also noteworthy that, unlike HDVs, the negative impact of panic and potentially irrational behavior of human beings (throughout emergencies) upon post-shock transfers can be effectively curbed by CAVs. The cost-effectiveness of the investment on that deployment of CAVs can be thereby further increased, for future urban communities.

Meanwhile, it shall also be noted that the casualty of urban communities under hazardous events can be profoundly impacted by an array of additional influential factors, e.g. the age, the underlying health condition, and the household income of those injured inhabitants, which have not been modelled in this study. Besides, as already highlighted by the case-study, apart from the local hospital system alone, the post-shock transfer and rescue will also be reshaped by the real-time functionality of the road network, the telecommunication system, as well as a host of other infrastructure systems embedded in the same region, given the looped interdependence within modern urban communities (Kröger and Zio 2011, Helbing 2013, Zhao and Sun 2021). By incorporating those factors into account, further research needs to be conducted to develop a more adaptive, coordinated and targeted strategy of post-shock rapid response, including emergency transfers, whereby the human, economic, and societal losses can be minimized, following the inclusive ABM framework proposed in this paper.

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