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AN INTEGRATED SIMULATION PLATFORM FOR CARDIAC ARREST RESPONSE SYSTEM

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ABSTRACT

In response to China's over 700,000 annual out-of-hospital cardiac arrests (OHCA), this paper presents a novel simulation framework integrating Geographic Information System, event occurrence probability models, and an agent-based model to efficiently formulate, optimize, simulate, verify, and analyze emergency response efficiency in cities. The framework supports large-scale, long-term city-level optimization and simulation, allowing for the evaluation of various dispatch algorithms, and deployment mechanisms. We offer insights into emergency first responder system design in Shenzhen, highlighting the significant impact of dispatch range, responder quantity, and skills ratio on survival rates. The experimental results indicate the maximum effective dispatch range of current dispatch strategy is 800 meters. As number of responders is less than 100, prioritizing an increase can significantly improve survival rates, with a maximum rise of 148%. However, when it exceeds 100, the focus should shift to augmenting the proportion of skilled responders, followed by the ratio of mobile responders.

1 INTRODUCTION

It is estimated that each year in China, over 700,000 people experience Out-of-hospital cardiac arrest (OHCA), and according to surveys, the survival rate for OHCA patients in China is only about 1.2% (Zheng et al. 2023). However, with timely treatment, the survival rate can be as high as 16% or even higher (Nichol 2008), indicating significant room for improvement. Such emergency medical events depend highly on timely pre-hospital interventions and effective emergency response systems (Cummins et al. 1991). Providing timely medical intervention within the first 'golden four minutes' of a cardiac arrest can significantly increase the chances of patient survival.

In the existing system, professional emergency teams generally cannot reach the scene within the four minute. This is due to the time required for preparation and the distribution density of hospitals, which cannot guarantee arrival at any location within the city in time. Consequently, the emergency first responders system (EFRS) concept has emerged. By training citizens to become responders, these individuals can provide initial medical intervention when a patient experiences a sudden condition. Utilizing the city-wide distribution of citizens significantly increases the likelihood of patients receiving aid within four minutes (Huang et al. 2021). The system leverages volunteers, also called emergency first responders, including highly mobile food delivery riders and flexibly moving walkers, to provide rapid medical intervention. Through targeted training for these volunteers in AED (Automated External Defibrillator) pickup, delivery, and operation, and CPR (Cardiopulmonary Resuscitation) operation, they are equipped to locate AEDs rapidly, deliver them to patients in the shortest possible time, and provide immediate emergency assistance.

EFRS is designed to compensate for potential delays in emergency medical team responses. However, the complexity of the urban road topology makes estimating rescue times imprecise. OHCA events are highly unpredictable, complicating effective personnel scheduling and resource deployment for authorities. For time-sensitive OHCA incidents, there is an urgent need to implement algorithmic optimizations in dispatch strategies and deployment policies to achieve shorter response times.

Simulation methods can overcome these challenges by modeling specific circumstances of events across different regions and settings, depicting each responder's characteristics in detail, repeatedly verifying and optimizing various strategies. This study introduces a simulation framework integrating Geographic Information System (GIS), an event occurrence probability model, and an agent-based simulation model. The GIS module incorporates real-world building data and road network structures, making all simulated movement patterns more closely mirror reality, thus enabling more accurate estimates of response times. Additionally, an event occurrence probability model is designed to more accurately reproduce the locations and timings of OHCA incidents, allowing decision-makers to pre-plan resource and personnel deployment. Ultimately, the simulation framework can incorporate various dispatch algorithms and deployment policies, conducting repeated experiments to validate the efficacy of the rescue.

We implement the simulation framework to comprehensively simulate and explore the operating mechanism of the EFRS, optimizing the system's resource deployment and allocation based on simulation experiments and analytical results. We have collaborated with experts from the Shenzhen technology institute of urban public safety to discuss the core logic and parameter settings of our model. These settings have undergone rigorous review by domain experts to ensure the logical coherence and practical applicability of our model design. The main contributions of our study can be summarized as follows:

1. We developed a novel simulation framework that comprehensively and meticulously models OHCA by integrating a set of realistic modules. It enables a more practical and accurate simulation and a deeper understanding and analysis of such emergency events, facilitating further optimization of existing systems.
2. The simulation framework also boasts significant extensibility, supporting city-level large-scale, long-term simulation analyses. Users can embed various rescue mechanisms, deployment, or dispatch algorithms and strategies to evaluate rescue performance, providing a powerful analytical tool for urban emergency management.
3. We provide valuable insights into EFRS design and achieve significant improvements in deployment strategy across dispatch strategy's effective range, the influence of responder numbers, and the ratio on survival rates for the current system in Shenzhen.

The rest of the paper is organized as follows. Section 2 includes a literature review of the Emergency First Responder System. Section 3 provides a thorough description of the simulation framework and agent behavior rules. Section 4 contains a detailed introduction to the experimental design and parameter settings. Section 5 discusses the experimental results and practical insights for EFRS design. Section 6 concludes this work and highlights future directions.

2 LITERATURE REVIEW

OHCA events are widely scrutinized due to their distinctiveness, presenting significant challenges for effective planning. Currently, Monte Carlo simulation methods are extensively applied to investigate details and simulate the occurrence of events, thereby providing guidance for real system design. Wei et al. (2020) explore strategies to improve the survival outcomes of OHCA patients under limited budget conditions through simulation, particularly emphasizing the importance of Automated External Defibrillators (AEDs) and bystander intervention. Van Den Berg et al. (2024) employ the Monte Carlo simulation method and highlight the crucial influence of alert policies and volunteer responder density on emergency response efficiency. Cairns et al. (2011) develop a Monte Carlo simulation model to simulate potential impacts across different geographic areas. Besides using Monte Carlo simulation to analyze the emergency response system, there are also some research using optimization methods. van den Berg et al. (2021) introduce the use of optimization to gain optimal allocation of volunteers and provide guidance for volunteer recruitment. Cao et al. (2023) formulate the joint scheduling problem of AEDs and multiple types of first responders with coordination as a mixed integer programming model, aiming for reduced response times and improved patient outcomes. Chan et al. (2018) propose a data-driven optimization model for AED deployment in public areas and emphasize the improvements in the accessibility of AEDs from the consideration of uncertainty in patients' locations.

Previous studies implement Monte Carlo simulation and optimization methods to address the intricacies of emergency response for OHCA, with a shared goal of enhancing survival rates through improved system design and resource distribution. Notwithstanding, to our knowledge, there has yet to be an exploration into the utilization of agent-based simulation for this critical area. While Monte Carlo simulation is strong for risk and uncertainty analysis and optimization methods are powerful for finding the best solutions under certain constraints, agent-based simulation is particularly powerful for understanding the behavior of complex adaptive systems and exploring the impact of individual-level changes on collective outcomes. Furthermore, agent-based simulation is also well-suited for incorporating geographic information and operating a flexible experiment environment. Therefore, this research employs an agent-based simulation model to mimic the events of out-of-hospital cardiac arrest, detail the heterogeneity of each responder, and reflect real-world scenarios. Such heterogeneity could be a key factor affecting the system's effectiveness and a critical consideration for system optimization. Moreover, the system integrates actual GIS data, enabling a more accurate simulation of the responders' movement trajectories during the rescue process.

3 METHODOLOGY

This study aims to explore how the behavior of responders in the EFRS and the deployment strategies of the call center affect the effectiveness of the rescue through the proposed framework. Furthermore, we furnish insights into the prevailing deployment strategies by experimenting with different parameters such as dispatch range, responder density, and the ratio of responder types.

3.1 Framework Structure

The simulation framework proposed in this paper, as shown in Figure 1, integrates GIS, a probability model of event occurrence, and an agent-based simulation model. Upon inputting the latitude and longitude of the simulation environment, the GIS module creates simulation grids and extract relevant information about buildings and road networks using OpenStreetMap (OSM). Subsequently, the probability model of event occurrence will utilize these extracted data to construct a probability distribution of events occurring within the area. After the environment setup is complete, the framework will define and generate agents for the simulation. Finally, the effectiveness of the proposed configuration is evaluated through a series of indicators such as patient survival rates, response time delays, and resource utilization efficiency.

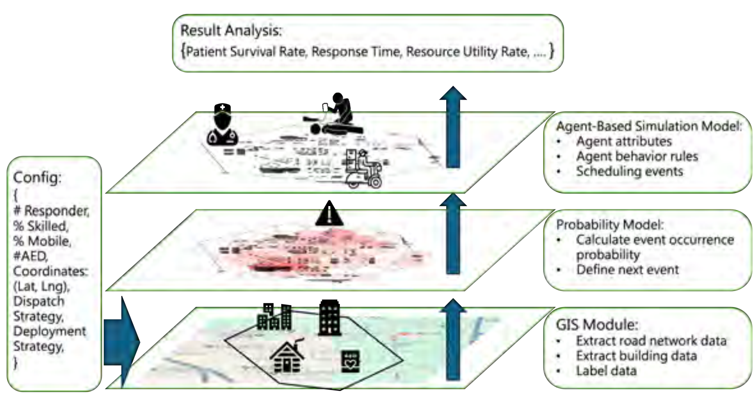
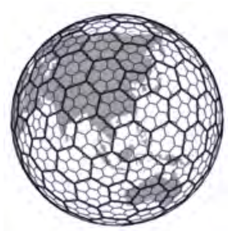
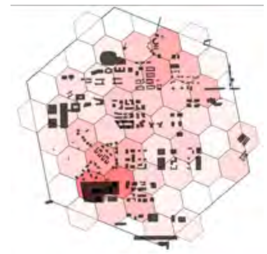


Figure 1: The architecture of the simulation framework.



(a) Partitioning Earth into identifiable grid cells.



(b) Distribution of building density in the grid.

Figure 2: H3 global grid system by Uber.

3.2 GIS Module

We utilize the H3 grid system developed by Uber Technologies (2019), which employs hexagonal grids to partition the globe into fixed regions, as illustrated in Figure 2a, to define the simulation environment. The selection of this system is based on its three distinctive characteristics: 1) The design of hexagonal grids ensures the uniformity of distances between grids, a feature particularly advantageous for future cross-regional dispatch or allocation. 2) The hierarchical nature of the system, which is divided into 16 levels. Each parent grid can be subdivided into seven smaller child grids, ranging from the largest at level 0 to the smallest at level 15. This structure facilitates efficient data aggregation and detailed spatial analysis through the nesting of multiple layers of hexagonal grids within each other.

3) The system's ease of accessing and storing is facilitated using fixed hexadecimal coding for grid indexing.

The simulation aims to model OHCA. Hence, the scale of the simulation environment is set within a range reachable within four minutes. Considering the average speed of electric scooters in China and the walking speed of an average adult male, we have set the primary grid size to level seven, with each side approximately 1.2 kilometers. Additionally, to balance the accuracy of event location and the computational burden of the simulation process, we selected a level nine child grid to determine the locations of events.

Finally, we extract relevant OSM data based on the grid's scope. This data includes the location, number, and type of buildings in the area and the distribution of the road network.

3.3 Probability Model

The second step involves defining the probability model for the occurrence of events. We employ the primary grid and the sub-grids in this stage to calculate probabilities. Faced with the challenge of acquiring actual population distribution data, we construct a fundamental hypothesis: the population distribution is proportional to the distribution of buildings. This implies that the sub-grids with a higher density of buildings contain more people, and correspondingly, the higher the probability of out-of-hospital cardiac arrest events occurring. We develop the corresponding probability model based on this hypothesis and the geographical data extracted from the previous step. As presented in Figure 2b, with darker red indicating higher density, correspondingly signifying a greater likelihood of OHCA occurrences.

Let N be the number of grids, and B_{ij} be the number of buildings of type j in grid i. P_i denotes the OHCA occurrence probability in grid i, shown in Eq (4). Each type of building j contributes a value k_j to the probability. In the experiment, however, we temporarily set the parameter k_j to be the same, due to the lack of relevant data to support the correlation between building categories and population.

$$P_i = \frac{\sum_j B_{ij} \cdot k_j}{\sum_{i=1}^{N} \sum_j B_{ij} \cdot k_j} \tag{1}$$

3.4 Agent-Based Simulation Model

The final step involves deploying agents and defining their behavioral rules and movement patterns. The agent-based simulation model is built in Anylogic version 8.8.0, as presented in Figure 3. The simulation model incorporates three types of agents. The first type is the responder, who is responsible for the rescue operations. Second type of agent, the call center plays a pivotal role in the simulation. Its primary duty is to dispatch the appropriate responders and resources according to selected deployment strategies. The deployment strategy of responders is central to optimizing resource utilization, directly relating to the response efficiency of emergency incidents and also impacting the success rate of rescue operations. The third type of agent is the patient, who is generated within the environment based on the probability model. After the event terminates, the system will calculate the corresponding patient survival rates to assist in evaluating the effectiveness of the system. The flow of each agent is demonstrated in Figure 4.

Figure 3: Simulation interface on Anylogic.

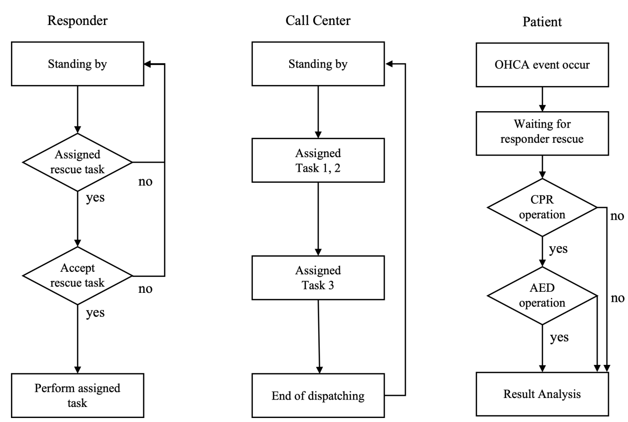


Figure 4: Agents' flowcharts during simulation.

3.4.1 Responders

The primary task of the responders is to implement preliminary intervention measures such as AED or CPR following the dispatch instructions from the call center. Responders are usually volunteers from the general public willing to participate in the program. They have become qualified responders through a series of training regarding the three tasks they are mainly responsible for, including the CPR operation, the AED operation, and the AED delivery task.

- Task 1: CPR operation - Rapidly reaching the scene to perform CPR.

- Task 2: AED operation - Directly leaving for the scene to conduct an AED operation.
- Task 3: AED delivery - Picking up and delivering the nearest AED to the patient's location.

In the simulation system, we differentiate between two types of responders: those with fixed workplaces and those with mobile workplaces. Responders with fixed workplaces include regular office workers, security guards, teachers, etc., who have relatively fixed work locations. Mobile workplace responders include food delivery riders, couriers, etc., whose work locations are not fixed and possess higher mobility. Based on the variations of work type, we assign distinct parameter settings to these two types of responders.

Firstly, regarding the mode of movement, responders with fixed workplaces will carry out the task on foot. In contrast, responders with mobile workplaces will use electric bicycles for transportation. Based on the average walking speed of adult males and the speed of electric bicycles in China, we have set the movement speeds for the two types of responders at 2 meters per second (Thorstensson and Roberthson 1987) and 7 meters per second (Lin et al. 2008), respectively. It is assumed that fixed workplace responders are more familiar with the locations of AED devices and do not need to park to enter buildings; hence, they require less time to locate AEDs than mobile workplace responders. While, they both need time to start providing response services after OHCA incidents occur (Johnson et al. 2022).

Furthermore, historical data suggests the average task acceptance probability for responders (Van Den Berg et al. 2024), based on which we set the task acceptance rate for all responders at 17%. Based on the analysis of personal data of responders, currently, approximately 60% of responders in Shenzhen are mobile responders and 70% of the total responders are skilled.

Lastly, regarding the task allocation for responders, given that all responders have completed the necessary training, the assignment of tasks will be contingent on their level of post-training skill proficiency. Consequently, we classify the responders further into skilled and unskilled categories. Skilled responders maintain their proficiency in emergency skills for up to two years following training, enabling them to perform all the three tasks mentioned above. In contrast, unskilled responders might solely be tasked with the delivery of AED devices to skilled responders. Table 1 summarizes the parameters used for responder agents in the simulation model.

3.4.2 Call Center

The call center holds dual responsibilities for both the pre-incident task of emergency responder deployment and dispatching rescue tasks during an emergency. Emergency responder deployment tasks first involve determining the dispatch range within which responders can achieve the optimal response time. Based on the planned dispatch range, the number of pre-deployed responders within each dispatch range is considered, as this factor also significantly affects the response time. Furthermore, the planning extends to the proportioning of different types of responders, taking into account how their various modes of movement and skill levels can influence response outcomes. Once these deployment parameters are implemented, the dispatch process is initiated by the call center. In the dispatch phase, it answers emergency calls without delay and is always on standby. Once an emergency call is received, responders are immediately dispatched.

Currently, the call center employs a multi-point dispatching strategy, meaning that multiple groups of responders are dispatched for the same incident to ensure that at least one group successfully arrives. The dispatch strategy is divided into two steps. Step 1 involves selecting skilled responders who have yet to be assigned tasks within a specified range of distance from the patient. The responders are chosen to perform either Task 1 or Task 2, performing CPR or executing an AED operation if an AED is ready. Step 2 involves selecting the remaining unassigned responders who are also within the specified range. Similarly, the individuals are assigned Task 3 to retrieve the nearest AED and deliver it to the patient's location.

Equation (2) represents the process of selecting suitable responders for Task 1 and Task 2. $S(r_i)$ denotes whether the responder is skilled, $A(r_i)$ indicates whether the responder has been assigned a task, $P(r_i)$ illustrates the position of responder, P_{patient} represents the position of patient, the expression $d(a,b)$ calculates the distance between a and b, and K represents the dispatch range. The current dispatch strategy implements a dispatch range of 500 meters, a judgment made by relevant agencies based on experience, but it still needs empirical and data support. We will conduct experiments on the dispatch range utilized by this strategy to observe the impact of range variations on patient survival rates. Only on this basis can we better plan for resource deployment. Correspondingly, Equation (3) signifies the process of selecting remaining suitable responders for Task 3.

$$R_{Task1,2} = \left\{ r_i \in R \;\middle|\; S(r_i) = \text{True} \wedge A(r_i) = \text{False} \wedge d(P(r_i), P_{\text{patient}}) < K \right\}, \tag{2}$$

$$R_{Task3} = \left\{ r_i \in R \;\middle|\; A(r_i) = \text{False} \wedge d(P(r_i), P_{\text{patient}}) < K \right\}, \tag{3}$$

3.4.3 Patient

Patients in OHCA incidents are generated through the event occurrence model in the second phase of the system. Once OHCA events occur, the system assumes that bystanders will immediately notify the call center and provide an accurate location. After that, as all dispatched responders arrive at the scene, the system calculates the patient's survival probability based on the responders' response times.

The formula for calculating survival rates in Eq (4) is derived from Valenzuela et al. (1997), indicating that any delay in intervention reduces the probability of survival. It considers the duration from the occurrence of an OHCA to the time of receiving AED (t_{aed}) and CPR (t_{cpr}).

We add a threshold for this function, namely the minimum time ($t_{\min}$), which is the minimum value between the AED response time and the CPR response time, i.e., $t_{\min} = \min\{t_{\text{aed}}, t_{\text{cpr}}\}$. If $t_{\min}$ is less than 4 minutes, the survival rate is calculated using the exponential decay function. On the other hand, suppose $t_{\min}$ is greater than or equal to 4 minutes. In that case, the survival rate is considered zero according to this study's parameters because, beyond this time frame, the patient's chances of survival significantly decrease, thus lacking statistical significance in the research context.

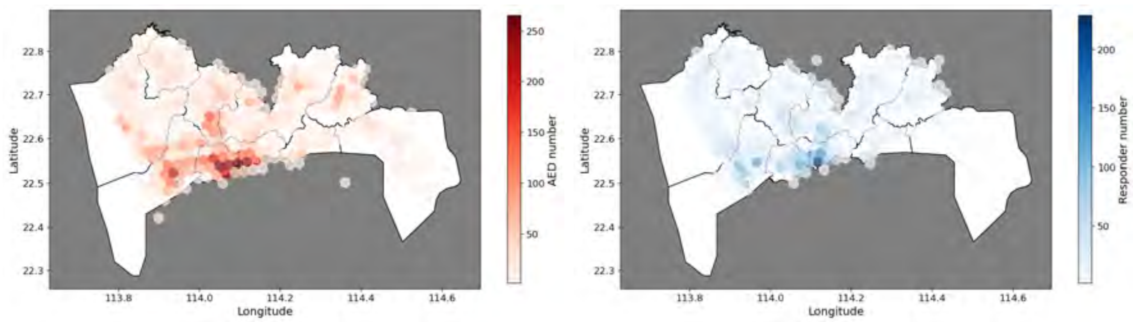
$$f(t_{\text{aed}}, t_{\text{cpr}}) = \begin{cases} (1 + e^{-0.26 + 0.106 \cdot t_{\text{aed}} + 0.139 \cdot t_{\text{cpr}}})^{-1}, & t_{\min} < 4, \\ 0, & t_{\min} \geq 4. \end{cases} \tag{4}$$

4 EXPERIMENTS AND DISCUSSIONS

4.1 Experiment Design

Given the complexity of adjusting AED deployment and its relatively static nature compared to responders, along with a lack of diverse characteristics influencing the success rate of rescue events, this paper utilizes actual AED distribution data from Shenzhen, as shown in Figure 5a. The study's focus is concentrated on optimizing the configuration of responders. The experiment selects four areas covering various scenarios, ranging from dense to sparse, to ensure the broad applicability and reliability of the experimental results. Among these, AED_0 signifies the most densely area, while AED_3 represents the least dense area.

Each experiment consists of 1000 randomly generated events. The configuration for each experiment is demonstrated in Table 1. The experiment is divided into three main parts. Experiment 1 examines the maximum dispatch range under the current dispatch strategy. This analysis provides an essential precondition for future studies on deployment optimization and EFRS design. Experiment 2 focuses on the deployment of personnel. It appears clear that an increase in the number of responders has an intuitive impact on improving patient survival rates, but it simultaneously incurs additional expenses associated with training and other factors, thus making it crucial to explore the relationship between the two through experimentation. The range for the number of responders varies from the average of 20 individuals per grid in Shenzhen City to the maximum of 240 currently in any grid across Shenzhen City (Figure 5b). Experiment 3 delves into the effects of the makeup of varied responder groups who, in turn, vary in their skills and mobility. The skilled responders can perform more tasks compared to unskilled ones, and mobile



(a) AED distribution. (b) Responder distribution.

Figure 5: Resource distribution in H3 L7 grid in Shenzhen.

responders can reach the patient's location faster than fixed ones. The ratios of these two types of responders among all responders significantly affect the patient's survival rate. Therefore, under circumstances with increasing total numbers of responders, we thoroughly investigate the impact of adjusting these two ratios in responder recruitment decisions on patient survival rates. The experiment is conducted solely in the densest AED areas of Shenzhen, with responder numbers of 20, 100 and 240.

Table 1: Simulation and experiment parameters setup

Agent	Parameter	Default value	Exp.1	Exp.2	Exp.3
Call center	Number	1	-	-	-
	Dispatch range (meter)	500	100$\sim$1200	Exp.1*	Exp.1*
	Dispatch number	All within range	-	-	-
Responder	Number	20	-	20$\sim$240	20, 100, 240
	Mobile ratio	60%	-	-	0% $\sim$ 100%
	Skilled ratio	70%	-	-	0% $\sim$ 100%
	Moving speed (m/s)	Mobile: 7	-	-	-
		Fixed: 2	-	-	-
	AED locate time (minute)	Mobile: UNIF(0, 3)	-	-	-
		Fixed: UNIF(0, 1)	-	-	-
	Prepare time (minute)	UNIF(0, 3)	-	-	-
	Task accept rate	17%	-	-	-
Patient	Number	1 each case	-	-	-

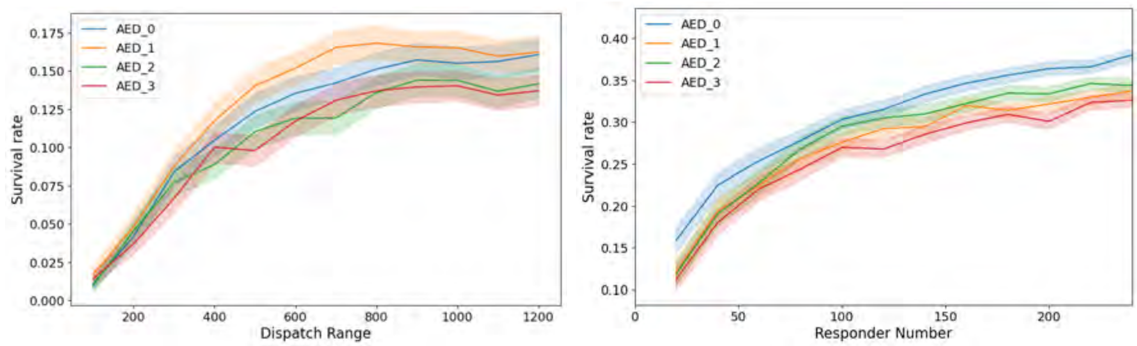
* represent result from the experiment

4.2 Impact of Dispatch Range on Survival Rate

From the results of Experiment 1 (Figure 6a), it is apparent that the maximum effective dispatch range can be identified under the current deployment configuration of the existing dispatch strategy. Expanding the dispatch range can effectively improve patients' survival rates, but this improvement is non-linear. Among all four representative areas, although survival rates vary along with different AED densities, the maximum effective dispatch range remains remarkably consistent for each area. When the dispatch range reaches 800 meters, the increase becomes less pronounced, with a maximum increase of only 2.8% and minimum increase of merely 0.3%.

This observation can potentially be ascribed to the fact that nearly all dispatchable responders capable of accepting the task and reaching within the four-minute window are located within 800 meters. Few additional successful response services can be provided by responders beyond that. For walking responders, it is challenging to arrive within four minutes for distances over 800 meters. While mobile responders can theoretically cover the distance in a straight line, the necessity of moving through the actual road network in the real world and our simulation framework may result in their inability to arrive within four minutes.

In conclusion, drawing upon both theoretical experiment findings and practical application insights, the maximum effective dispatch range for the EFRS under current deployment configurations of the existing dispatch strategy is approximately 800 meters. Subsequent experiments proceed under this specific setting.



(a) Dispatch range.

(b) Responder number.

Figure 6: Impact of dispatch range and responder number on survival rate.

4.3 Impact of Responder Number on Survival Rate

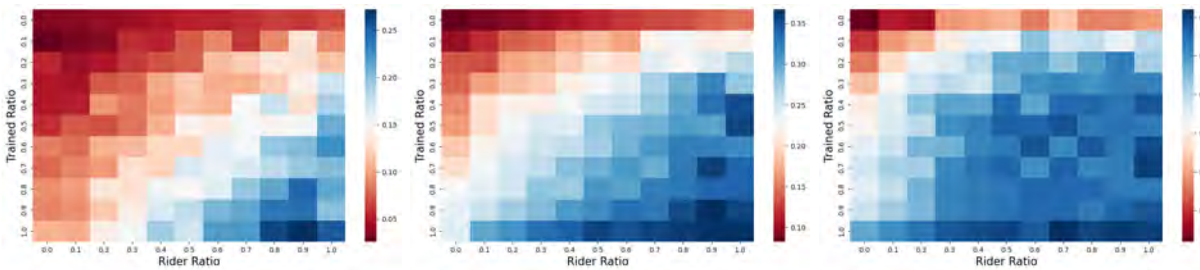
Experiment 2 (Figure 6b), reveals an increasing relationship between the total number of responders and patient survival rates. Increasing the number of responders can provide the call center with more alternatives, potentially reducing the distance between responders and patients, thereby effectively improving patient survival rates. Experimental results indeed corroborate this intuitive insight, with survival rates trending upward as the number of responders increases from the current average of 20 to 240 in each area.

However, it should be noted that this growth relationship also exhibits non-linearity. When the number of responders increases from 20 to 100, the survival rate can increase by up to approximately 148.91% and even the smallest change resulted in a 90% improvement, but from 100 to 240, the increase is at most only 16.57%. This suggests that merely increasing the number of responders does not invariably yield identical outcomes in terms of enhancing rescue rates.

Therefore, we further explore the correlation between the total number of responders and patient survival rates. The Spearman correlation coefficients in each area are '0.5361, 0.4547, 0.4599, 0.4090', with the p-value less than 0.005. This indicates that the total number of responders is not entirely positively correlated with patient survival rates, suggesting that the total number of responders is not the only factor affecting patient survival rates. This finding lays the foundation for the design of Experiment 3.

4.4 Ratio of Different Responder Types

In Experiment 3, we modify the ratios of different types of responders to observe their impact on patient survival rates. The experiment is initially conducted with 20 responders, aligning with the average number of responders per Shenzhen's H3 level 7 grid division. The results, as illustrated in Figure 7, indicate that given a fixed total number of responders, the survival rate of patients tends to escalate when the ratio of skilled and mobile responders is higher. This phenomenon is noticeable in the heatmap, where the color gradually shifts from red to blue with increasing proportions. Moreover, when one proportion is fixed, increasing the proportion of skilled responders has a more significant improvement effect than increasing the proportion of mobile responders.



(a) 20 responders. (b) 100 responders. (c) 240 responders.

Figure 7: Survival rate under different ratios of responders within varying numbers.

Furthermore, with 100 and 240 responders, even without any mobile responders and all being skilled responders, patient survival rates of about 24% and 34% can still be achieved, further proving the significant impact of skilled responders on the first responder system. Compared to the current configuration of responder proportions, prioritizing an increase in the proportion of skilled responders can enhance survival rates by up to 16%; subsequently increasing the proportion of mobile responders can further improve survival rates by 3%. The reason for the more significant impact of skilled responders compared to mobile responders is that skilled responders can directly affect the treatment received by patients while mobile responders mainly enhance survival rates by reducing response time.

In addition to comparing the significance level of the effect on survival rates between skilled and mobile responders, disparities also exist within the experimental results as the number of responders varied. Results show that with 20 responders, achieving the maximum survival rate of 27% is possible if the proportion of mobile responders reaches 90% and the proportion of skilled responders peaks at 100%. In contrast, when the number of responders is 240, the proportion of mobile responders only needs to reach 70% to achieve the maximum effect of 41% in survival rate. Hence, an inference can be drawn that the lower the redundancy of responders, the higher the requirement for skill proficiency and moving speed of responders.

5 CONCLUSION AND FUTURE WORK

The meager survival rates of OHCA events have gradually become a focal point of widespread public concern. As a potentially effective treatment for OHCA, the implementation of EFRS has yielded positive outcomes across numerous global regions, signifying its benefits. However, efficiently deploying emergency resources in this system remains a significant challenge for cities newly introducing this system, marking an urgent requirement for a systematic method to provide guidance and direction.

Our innovatively designed simulation framework, integrating agent-based simulation models, event occurrence probability models, and GIS, considers complex characteristics of OHCA treatment within the EFRS. This relatively holistic design enhances the framework's reliability and offers an optional solution to the aforementioned challenge. The high extensibility of this simulation framework enables us to adjust and experiment with dispatch and deployment strategies, providing reliable insights for urban-level managers. We carry out initial experiments in select regions of Shenzhen City, and the results provide practical suggestions for future planning in these areas. The completion of these experiments also substantiates the potential feasibility of more intricate deployment planning validation and optimization for OHCA incidents within our framework.

The experimental findings demonstrate that enhancing both the dispatch range and the number of responders can improve the rescue rate, though this enhancement is nonlinear. For dispatch range, can only achieve a marginal rescue rate improvement of up to 2.8%. Hence, this study suggests setting the maximum effective dispatch range at 800 meters and performing subsequent deployment experiments on this basis. A similar nonlinear relationship exists regarding the deployment number of responders. When the number of deployed responders in a fixed range is under a hundred, prioritizing an increase in numbers can enhance patient survival rates by up to 148%. However, once the number exceeds 100, the increase marginally impacts survival rates, with a maximum increase capped at approximately 16.57%. Under this circumstance, incorporating other factors into consideration may be beneficial.

Besides, Figure 5b clearly shows the current recruitment situation of respondents, with merely five grids having more than 100 responders and the average number being only 20. Even discovering that the number of responders significantly affects survival rates, increasing the number remains challenging. Therefore, we further explore the effects of variations in responder ratios on survival rates. The experimental results indicate that given a fixed total number of responders, the survival rate of patients tends to increase when the ratio of skilled and mobile responders is higher. The effect of optimizing the ratio of skilled responders is much more significant, with the potential to boost survival rates by up to 16%. Further increasing the ratio of mobile responders can contribute an additional 3% enhancement in survival rates. A concurrent observation is that when the redundancy of responders is lower, the demands for skill proficiency and responder mobility are correspondingly higher.

In conclusion, we encourage decision-makers to consider both the total number of responders and individual characteristic differences during the process of responder deployment and EFRS design. When a sufficient pool of recruitable responders is available, the priority should be increasing the number of responders. Conversely, when further increment in the number of responders becomes challenging, or when the number of responders is adequately high, attention needs to shift towards optimizing the ratios of different responder types.

Future research directions include further integration and optimization of GIS, considering the impact of traffic flow and special events on emergency response times, and dynamically adjusting deployment strategies. Analyzing and anticipating volunteer cooperation patterns from the perspective of complex networks could also be a meaningful extension of the simulation model (Xiu et al. 2024). Additionally, the extension and diversification of simulation models, such as more types of responders and different environmental conditions, can also be explored to provide a more comprehensive solution for emergency management. Moreover, efficient scheduling algorithms can be developed to further enhance the efficiency of the system, e.g., branch-and-price, adaptive large neighborhood search (Hua et al. 2022) , reinforcement learning (He et al. 2023) , etc.

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