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Modeling uncertain task compliance in dispatch of volunteers to out-of-hospital cardiac arrest patients

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ABSTRACT

In countries such as Sweden, Italy, Switzerland, and the Netherlands, projects in which volunteers are dispatched to out-of-hospital cardiac arrest (OHCA) patients with the use of mobile phones exist. Once an OHCA case is reported, a notification is sent to the mobile phones of registered volunteers that are in the vicinity of the patient. These projects mostly use static dispatch methods to determine which volunteers should be sent directly to the patient and which ones should pick up an automatic external defibrillator (AED). However, such schemes do not consider uncertainties associated with these task assignment decisions (e.g., if volunteers will do as instructed, or do something else). In this paper, we propose a method for optimized task assignment and dispatch of volunteers to OHCA patients that considers the uncertainty related to volunteers' actions once assigned a task. We then compare the results of our method to those of a static dispatch method used in an ongoing mobile phone volunteer dispatch project in Sweden and validate them using simulation. Furthermore, we perform a sensitivity analysis on several parameters to investigate their effect on the performance of the proposed method. With the comparative results we show that the proposed method may help increase the survivability of OHCA patients.

1. Introduction

Emergency services face various challenges, ranging from limited available resources, enforced budget cutbacks, and long travel times to reach sparsely populated areas, to increasing demand due to various reasons, such as aging population, more traffic, and increasing urbanized areas (Yousefi Mojir & Pilemalm, 2016). Additionally, larger scale emergencies resulting in a greater number of affected individuals require emergency organizations to utilize their resources more extensively (Yu et al., 2019). One solution to these challenges is to introduce new types of resources that do not incur any notable additional costs for the emergency services.

Volunteers are emergency response resources that have been gaining increasing interest in the past few years. They might reach affected people sooner than professionals, and the cost for utilizing them is lower. Many initiatives utilizing semi-organized volunteers for daily emergencies (i.e., events that occur frequently but have a low magnitude of consequence), such as cardiac arrest and other medical emergencies, traffic accidents, and building fires, exist and the number of such initiatives is increasing. These volunteers are people registered in an information system, and might possibly have relevant training and equipment, but have no formal responsibilities. Examples of such initiatives include Missing People Sweden (Missing People Sweden, n.d.), volunteers in rural villages who in collaboration with the fire and rescue services perform first response (Ramsell et al., 2017), and cardiopulmonary resuscitation (CPR) trained citizens who can also utilize automated external defibrillators (AED) in case of an out-of-hospital cardiac arrest (OHCA) in countries like Sweden, the Netherlands, Denmark, and several other countries in the world (Andelius et al., 2020, 2021; Oving et al., 2019; Scquizzato et al., 2020). It is important to notice that these volunteers are not perceived as resources that should replace regular emergency services. Therefore, emergencies for which no volunteer is available in the vicinity of the case (or responds to the alert) can occur.

In the OHCA projects, a mobile phone positioning system is utilized to identify the volunteers in the vicinity of the patient (up to a specific maximum number of volunteers), and simultaneously with the dispatch of emergency medical services (EMS), an automatically generated notification is sent to the relevant volunteers (Ringh et al., 2011, 2015). Two main tasks for the volunteers exist: (1) to collect an AED en route to the patient, or (2) to go directly to the patient to perform CPR. Although the positions of the volunteers can be assumed sufficiently well-known, it is not trivial to decide who should do which of the two tasks.

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Uncertainties associated with the response and task compliance of volunteers complicate the determination of task assignments for each of the volunteers.

The aim of this work is to develop a method for dispatch of volunteers to OHCA patients in order to shorten the time to basic CPR and early defibrillation using an AED before EMS arrival (factors that are associated with an improved chance of survival for OHCA patients (Metelmann et al., 2021; Nehme et al., 2019; Pijls et al., 2016; Stroop et al., 2020)), while taking into account uncertainties regarding volunteers' task compliance.

Thus, in this study, we explicitly model uncertainties associated with the volunteers' actions once assigned a task. This is done by considering the probabilities of mission abort, noncomplying actions, and full compliance with instructions for each task assignment. The developed method determines how the available volunteers should be dispatched in order to maximize the survivability of the OHCA patient, as estimated by a survival function. Then, we investigate whether the proposed dispatch method leads to an improved survival chance for OHCA patients by comparing it to the dispatch method currently used in one of the OHCA volunteer projects. To determine the feasibility and robustness of the results obtained from both methods, we implement a simulation model capable of considering additional stochastic factors that could not be directly included in our proposed dispatch method. We also perform sensitivity analysis on some of the parameters to investigate how the results are affected.

The rest of the paper is organized as follows. In Section 2 we present a summary of related literature as well as the positioning of this paper with respect to the literature. We dedicate Section 3 to problem description. In Section 4 we provide the description of the task assignment and dispatch method, followed by a description of the simulation model in Section 5. We describe the input data in Section 6. We present the computational results in Section 7 and the sensitivity analysis in Section 8, continuing with discussions in Section 9. Finally, with Section 10 we close the paper with conclusions and future research directions.

2. Related work

Considering the broadness of the literature in the context of volunteer management, in this section, we discuss the literature that is most relevant to this study.

To utilize volunteers in the best possible way, it is important to know their capabilities and one way is to evaluate volunteers who have previously participated in response operations. Authors of two descriptive studies, Earl et al. (2003) and Earl et al. (2005), investigated the knowledge and skills of emergency management volunteers at outdoor music festivals. Groh et al. (2007) described and evaluated characteristics of volunteers that have responded to emergencies in the framework of the North American Public Access Defibrillation trial. These authors concluded that there is a higher probability that volunteers who have had previous emergency training would participate in response to medical emergencies.

When volunteer management systems are already in place, volunteers should get the relevant training for acquiring or maintaining relevant capabilities (Sun & Wallis, 2012), while emergency managers take advantage of modern technologies to support the efficient utilization of volunteers (Schönböck et al., 2016). Jaeger et al. (2007) explored the usage of Internet and mobile communication devices for information sharing as well as for the coordination of volunteers and residents in response to a major disaster. Romano et al. (2014), on the other hand, introduced a mobile phone application that includes a feature for volunteer registration of skills, and thereby, it enables the emergency management operation center to retrieve the specific capabilities of each volunteer. The application also facilitates remote supervision of volunteers by the emergency management operators. McLennan et al. (2016) discussed that traditional volunteering activities decrease because of changes in lifestyle and values over time. Meanwhile, the introduction of new communication technologies has stimulated both digital and digitally enabled volunteering activities.

Authors of several qualitative works in the literature have focused on task assignment, crowd tasking and crowdsourcing, such as, Neubauer et al. (2013), Liu (2014), Auferbauer et al. (2016), and Havlik et al. (2016). In contrast to these qualitative studies, a quantitative study in the field of volunteer management is Falasca and Zobel (2012). Based on a set of principles from the volunteer management field, these authors proposed a multi-criteria optimization model for task assignment to individual volunteers as well as for groups of volunteers in disaster response. They presented a bi-objective optimization model, aiming to minimize (1) the total cost of task shortages, and (2) the total number of undesired task and time block assignments. Other quantitative studies are those of Lassiter et al. (2015) and Khalemsky and Schwartz (2017). Lassiter et al. (2015) proposed a robust bi-objective optimization model to assign tasks to volunteers after a disaster with the objective of minimizing total unmet demand and maximizing preference of volunteers. The proposed model seeks to match tasks to volunteers with respect to their skills. Khalemsky and Schwartz (2017) used simulation to provide a model to evaluate the benefits of using first responders, such as volunteers, in emergency response and comparing these benefits and their potential performance to regular emergency medical services. While the number of quantitative works related to dispatch of volunteers, especially in daily emergencies, is low, many exist for the optimal dispatch of ambulances (e.g., Andersson and Värbrand (2007), McLay and Mayorga (2013), Jagtenberg et al. (2017), and Enayati et al. (2018)), and optimal placement or deployment of AEDs (e.g., Tsai et al. (2012), Bonnet et al. (2015), Chan et al. (2016), and Lee et al. (2019)). Some of these authors have also considered the presence of bystanders in their modeling.

Volunteers can take part in different types of emergencies, but one, that several ongoing projects focus on, is OHCA. Among these projects, SMS lifesavers (SMS Lifesavers, n.d.) started in 2010 as a research project in Stockholm, Sweden, and is now operational in seven regions/counties in Sweden. SMS lifesavers are registered volunteers contributing in OHCA cases.

The presence of publicly available AEDs provides the chance of shortened time from collapse to first defibrillation (Culley et al., 2004), and might double the survival chance compared to when the patient only receives help from a CPR-trained lay rescuer without an AED (Groeneveld & Owens, 2005). Several studies have considered the use of mobile phones to dispatch volunteers to OHCA cases (e.g., Zijlstra et al. (2014), Ringh et al. (2015), Pijls et al. (2016), Capucci et al. (2016), Caputo et al. (2017), and Berglund et al. (2018)), and the results of those studies showed that this can potentially reduce time to initiation of basic CPR and first defibrillation. Other studies such as the work of Stroop et al. (2020) also indicated that simultaneous dispatch of CPR-trained volunteers and EMS to OHCA patients can reduce response time and resuscitation-free intervals and may have a positive impact on the survival to hospital discharge rate for OHCA patients. Despite very low-certainty evidence, the 2020 International Consensus on Cardiopulmonary Resuscitation and Emergency Cardiovascular Care Science With Treatment Recommendations (Nolan et al., 2020), made a strong recommendation that volunteer programs should be implemented. Consequently, the European Resuscitation Council Guidelines 2021 (Semeraro et al., 2021) highly encourage European countries to implement mobile phone dispatched volunteer programs to reduce the time to start of CPR and defibrillation.

Cummins et al. (1991) formulated the concept of "chain of survival" comprising a sequence of events that take place in response to incidences of sudden cardiac arrest: (1) to recognize suspected sudden cardiac arrest, (2) to gain access to EMS for activation, (3) to commence basic CPR, (4) to deliver defibrillator shocks, (5) to intubate, and (6) to administrate adequate medication intravenously. A short time to sequence completion improves the probability of survival. Cummins et al. (1991), Herlitz et al. (1994), Valenzuela et al. (2000), and Waalewijn et al. (2001) all emphasized the importance of early basic CPR, especially the immediate start of bystander CPR that increases survival rates for OHCA patients. The essential value of early basic CPR is to maintain viability in vital organs (Cummins et al., 1991) and to generate a temporary restoration of cardiocerebral and transpulmonary circulation and respiration by continuous repetition of chest compressions and ventilations, respectively (Lurie et al., 2016). A three minute delay to start basic CPR diminishes the chance of survival by up to 50 percent (Waalewijn et al., 2001).

A survival function can be used to estimate the chance of survival from an OHCA, given a set of relevant factors, such as the time interval between collapse and CPR, the time interval between collapse and the first defibrillator shock, the time interval between collapse and initiation of advanced cardiac life support (arrival of first ambulance), initial arrhythmia, CPR initiated by a bystander, and the patient's age (Herlitz et al., 1994; Larsen et al., 1993; Valenzuela et al., 1997; Waalewijn et al., 2001). Numerous authors focus on the study of survival of OHCA patients, especially in the medical field of research, with the aim to determine critical survival factors and to develop a survival function. However, the number of quantitative studies in which a survival function is used in the model is more scarce; for example, Erkut et al. (2008) use a survival function in their maximal covering location problem and Matinrad et al. (2019) in their deterministic volunteer dispatch model.

We contribute to the current literature in three ways:

- Recently, various studies have focused on the practical utilization of volunteers in OHCA response systems. However, to the best of our knowledge, none has focused on the development of a dispatch model. We, inspired by the works of Ringh et al. (2011, 2015), propose a method for optimized dispatch of volunteers to OHCA patients that considers the uncertainty of task compliance.
- To our knowledge, a limited number of quantitative research studies on volunteer management exists, especially for daily emergencies. In this respect, the most relevant to our work are those of Falasca and Zobel (2012) and Lassiter et al. (2015), which focus on task allocation to volunteers in response to disasters. Compared to these works, we focus on daily emergencies, where the response time is of vital importance. Thus, we also consider an estimate, based on real data, of the volunteer response time to an event.
- Using real data from the SMS lifesavers project, we show that it is possible to improve the survival probability for OHCA patients using a dynamic dispatch method, compared to the static method that is used today.

3. Problem description

For an OHCA event, a set of volunteers who can be dispatched to the patient exists. However, at the time of the event, the availability of each volunteer is unknown. In the SMS lifesavers project, which we use as a case, the first step is to assess the availability and willingness of the volunteers to take part in the current case by sending an event notification, without any instructions, to the n (equal to 30 at the time of this study) volunteers closest to the patient (Ringh et al., 2011, 2015), according to the last known position. Once a volunteer indicates his/her availability, and thus, accepts to take part in response to the current case, the position is updated based on the phone's current location, and (s)he will be assigned one of two tasks: (1) to pick up an AED or (2) to go directly to the patient. Within the SMS lifesavers project, at the time of this study, this was done by using a static first-accept-first-assigned rule block: A-A-D-A-A, where A means to pick up an AED and D is to go directly to the patient, that repeats until all volunteers receive an assignment (maximum 30 volunteers and minimum of 1). Thus, the first two volunteers are sent to pick up an AED, while the third is sent directly to the patient, and the next two are sent to pick up an AED. The assignment rule block repeats until all volunteers that indicate their availability are assigned to do one of the two tasks, in the order that they have responded to the primary notification. If any of the volunteers' estimated travel time to the patient is longer than a certain predefined threshold (i.e., the cutoff time), which may happen if the initial position was old, (s)he will not receive any task assignment. After the task assignment, the volunteers may or may not comply with the assignment, which leads to two risks. First, a volunteer may do the opposite action (e.g., one assigned to an AED can go directly to the patient instead). Second, a volunteer may abort the mission at any time after accepting it.

Regarding the set of AEDs, their locations are assumed known at the time of the dispatch. Although some of them may not be accessible, such as in closed shops, this information is also available beforehand. However, there is still a risk that the information is not updated, or that the AED is missing or malfunctioning. Moreover, travel times may vary significantly depending on the volunteer, road, access to a vehicle, weather conditions, or other conditions, which may be unknown at the time of dispatch.

Previous studies have shown that in many cases, CPR is started by bystanders before the arrival of volunteers or EMS (Pijls et al., 2016; Ringh et al., 2015). However, when making the volunteer task assignment, depending on the design of volunteer alert system (e.g., if it is fully automated), this information might not be available, and thus, impossible to take into account in the decision making. Also, unlike the registered volunteers who have some level of training in performing CPR and using an AED, bystanders may have no training at all, and may have to rely on instructions by the dispatcher at the emergency call center. Therefore, there is a risk that the quality of the CPR started by a bystander is lower than that of a volunteer. In addition, the exact start time of bystander CPR may be unknown at the time of dispatch of volunteers.

3.1. Problem assumptions and statement

As already noted, several uncertain elements affect the outcome of a volunteer assignment. In this work, we focus on the volunteers' decisions after they have been assigned a task, that is, we explicitly model the probabilities that they abort a mission, that they do not follow the given instructions, or that they comply with the assignment. Thus, in the dispatch method, travel times and AED availability (and functionality) are considered deterministic and known (the feasibility of the travel times assumption is then tested using the simulation model). We assume that an assignment decision has to be made as soon as a volunteer has accepted a mission. Once a decision for assignment of a volunteer has been made, it will not be changed at a later stage. In addition, when making a dispatch decision and calculating the survival chance of patients, we assume that no bystander is performing CPR.

The Dynamic Probabilistic Volunteer to OHCA patient Dispatch (DyPVOD) problem (an online problem) can be stated as:

Dynamically assign one of two tasks {pick up an AED, go directly to patient} to volunteers, in order to maximize the survival chance of the patient, given uncertain information about future incoming acceptances and uncertain volunteer task compliance.

3.2. Problem notation and preliminaries

Assume that out of the n volunteers that the primary notification has been sent to, m volunteers will accept the mission, with $j \leq m$ signifying the j^{th} volunteer to accept.

Two possible assignments for each volunteer exist:

- A_j: volunteer j should pick up an AED
- D_j: volunteer j should go directly to patient

For each volunteer, there are three possible outcomes:

- O_j^A: volunteer j picks up an AED
- O_j^D: volunteer j goes directly to patient

- O_j^R: volunteer j aborts the mission

The probability for each outcome is conditional, depending on the assignment, for example, $P(O_j^D|A_j)$ is the probability that volunteer j will go directly to the patient when being assigned to pick up an AED. Moreover, $P(O_j^A|A_j) + P(O_j^D|A_j) + P(O_j^R|A_j) = 1$ holds (analogously for assignment D_j). For evaluation purposes, all the probabilities can be calculated from historical data. Moreover, we assume that the probability for a specific outcome is the same for all volunteers.

When l volunteers ($l \le m$) have been dispatched, the number of possible outcomes becomes 3^l, that is, all possible combinations of the individual outcomes. Given that the outcome for each volunteer (i.e., the action of each volunteer) is independent of the other volunteers, and volunteers are assumed independent and not in contact with each other, the probability for a joint outcome (the joint probability), can be calculated as the product of the individual probabilities, for example:

$$P((O_1^D|A_1) \cap (O_2^A|A_2)) = P(O_1^D|A_1)P(O_2^A|A_2) \tag{1}$$

The survival probability of the patient is calculated using the survival function from Matinrad et al. (2019):

$$f(t^*, s^*) = \frac{1}{1 + e^{(-1.3614 + 0.3429t^* + 0.18633s^*)}} \tag{2}$$

where t^* is the time until the start of the first CPR and s^* is the time until the first defibrillation using an AED. The survival function is primarily based on a logistic regression model from Valenzuela et al. (1997), with updated parameters from the study population data in Waalewijn et al. (2001). We disregard the time between arrival of a volunteer and the start of CPR or the use of AED (i.e., the setup time), for example, the time until defibrillation using an AED is considered equal to the arrival time of a volunteer with an AED. We assume this, because, to the best of our knowledge, data for estimating the setup time is insufficient. It should be noted that if no volunteer picks up an AED, s^* will be equal to s^{max}, which is an upper limit for the time to defibrillation that for example can be set to the arrival time of EMS. Similarly, t^{max} is the upper limit for time to CPR. Furthermore, if a volunteer with an AED is the first help on the scene, s^* and t^* will be the same and equal to the arrival time of the first arriving volunteer. Because someone bringing an AED is also capable of performing CPR, we have, $t^* \le s^*$.

Each outcome is also associated with a response time to the patient. Let T_{o_j} be the time until volunteer j reaches the patient, given outcome o_j ($o_j \in \{O_j^A, O_j^D, O_j^R\}, j = 1, \cdots, m$), including both travel times and time to acceptance (i.e., time from notification until acceptance by the volunteer).

$$f(t^*, s^*|A_1) = f(t^*, s^*|O_1^A) * P(O_1^A|A_1) + f(t^*, s^*|O_1^D) * P(O_1^D|A_1) + f(t^*, s^*|O_1^R) * P(O_1^R|A_1) \tag{5}$$

$$f(t^*, s^*|D_1) = f(t^*, s^*|O_1^A) * P(O_1^A|D_1) + f(t^*, s^*|O_1^D) * P(O_1^D|D_1) + f(t^*, s^*|O_1^R) * P(O_1^R|D_1) \tag{6}$$

4. Sequential probabilistic task assignment and dispatch method

To solve the DyPVOD problem, we developed a Sequential Probabilistic Task Assignment and Dispatch (SePTAD) method. At each decision point, that is, when a new volunteer (e.g., j) accepts the notification, the available information consists of the number of volunteers that have already accepted the notification (j-1), and what tasks they have been assigned to. The steps in the method for deciding whether to send volunteer j directly to the patient, or to pick up an AED are as follows:

1. Every possible action of every previous volunteer, as well as volunteer j's, is considered, which leads to 3^j possible outcomes. In each combination of possible outcomes, the arrival times of the volunteers, $T_{o_i}(o_i \in \{O_i^A, O_i^D, O_i^R\}, i = 1, \cdots j)$, are used to determine t^* and s^*. Thus, t^* and s^* are calculated as follows:

$$t^* = \min_{i=1,\cdots,j|o_i \in \{O_i^D, O_i^A\}} \{t^{max}, T_{o_i}\} \tag{3}$$

$$s^* = \min_{i=1,\cdots,j|o_i \in \{O_i^A\}} \{s^{max}, T_{o_i}\} \tag{4}$$

2. For each combination of possible outcomes ($o_i \in \{O_i^A, O_i^D, O_i^R\}, i = 1, \cdots, j$), using the calculated t^* and s^* and the survival function (i.e., Equation (2)), the survivability of the patient is determined.
3. The joint probabilities for each of the 3^j outcome combinations are calculated. Because the assignment for volunteer j needs to be determined and the outcome probabilities are conditional on the task assignment, two sets of calculations are required ($2*3^j$). One set considers that volunteer j will be assigned to go directly to the patient (D_j), and the other to pick up an AED en route to patient (A_j).
4. For each combination, the survivability calculated in step (2) is multiplied with joint probability for each decision (A_j or D_j) calculated in step (3).
5. The final survivability for each decision (A_j or D_j) is calculated as the sum of the survivability for all combinations in step (4).
6. The decision giving the highest final survivability is selected as the task assignment for volunteer j.

For the first volunteer, the survival function is calculated for the three possible outcomes (i.e. O_1^A, O_1^D, O_1^R). For instance, the potential outcome O_1^D would give a survivability of $f(t^*, s^*|O_1^D) = f(T_{O_1^D}, s^{max})$, that is, t^* is set to the time it takes for volunteer 1 to reach the patient when going directly, and s^* is set to s^{max}. Thus, the survival chance if the first volunteer aborts the mission is $f(t^*, s^*|O_1^R) = f(t^{max}, s^{max})$.

The final survivability in this case is calculated as the joint probability multiplied by the related survivability, for decision A_1 and D_1:

Finally, the decision giving the highest final survival chance for the patient is selected, that is, the one satisfying $\max_{i \in \{A_1, D_1\}} f(t^*, s^*|i)$.

For the second volunteer, the survival function should be calculated nine (3^2) times for each decision since for each of volunteer 1 and volunteer 2 three possible outcomes can happen. Each joint outcome from the set $\{\{O_1^D, O_2^D\}, \{O_1^D, O_2^A\}, \{O_1^D, O_2^R\}, \{O_1^A, O_2^D\},$

$$\{O_1^A, O_2^A\}, \{O_1^A, O_2^R\}, \{O_1^R, O_2^D\}, \{O_1^R, O_2^A\}, \{O_1^R, O_2^R\}\}$$

, comprising of all possible joint outcomes, gives one specific t^* and s^*. The value of t^* is calculated as the minimum of all travel times to the patient, either directly or via an AED. Moreover, s^* is calculated as the minimum of all travel times where a volunteer picks up an AED. In the same way as for the first volunteer, if no volunteer picks up an AED, s^* will be equal to s^{max}. In addition, if none of the volunteers reaches the patient (i.e., both abort the mission), t^* will be set to t^{max} and s^* to s^{max}.

The joint probability for each outcome depends on the assignment for each volunteer. For example, assume that volunteers 1, 2, and 3 receive assignmentsA_1, D_2, A_3. One outcome (out of 27 possible outcomes) is O_1^R, O_2^D, O_3^A. Assuming independence, the joint probability for this outcome is calculated as:

$$P\left(\left(O_1^R|A_1\right)\cap\left(O_2^D|D_2\right)\cap\left(O_3^A|A_3\right)\right) = P\left(O_1^R|A_1\right)P\left(O_2^D|D_2\right)P\left(O_3^A|A_3\right) \tag{7}$$

where the individual probabilities on the right-hand side are derived from historical data, as we will detail in Section 6.

Thus, for the two possible decisions, A_j and D_j, it is possible to calculate the survival chance as well as the probability for the 3^j possible outcomes giving the final survivability for each of the two decisions:

$$f\left(t^*, s^*|A_j\right) = \sum_{i=1}^{3^j} f_i P_i^A \tag{8}$$

$$f\left(t^*, s^*|D_j\right) = \sum_{i=1}^{3^j} f_i P_i^D \tag{9}$$

where f_i and P_i^A in Equation (8) are the survivability and the joint probability of occurrence of outcome i, $i \in \{(O_1^D, O_2^D, \cdots), (O_1^D, O_2^A, \cdots), \cdots, (O_1^R, O_2^R, \cdots)\}$, given decision A for the j^{th} volunteer. As before, the decision giving the highest final survivability is selected.

5. Simulation evaluation

The methodology described in Section 4 can be used to calculate the expected survivability for any dispatch method, taking into account the task compliance uncertainty. However, it does not account for other stochastic aspects, like travel times. Thus, to evaluate the feasibility and robustness of the results from the dispatch methods, we developed a simulation model. From here on, the dispatch method used in the SMS lifesavers project at the time of the study will be called the original method.

5.1. Main simulation model

One simulation replication for one case (one dispatch) can be described by the following steps:

1. For each dispatched volunteer, do the following:
   a. Based on the outcome probabilities (conditioned on the assigned task), randomly draw one of the three possible outcomes (i.e., volunteer decisions: O^A, O^D, O^R).
   b. Depending on the drawn outcome, randomly draw a travel speed, and calculate the travel time to the patient with this speed. This time, together with the time to acceptance, will give the response time to the patient. It can be the time to the patient without AED (O^D), with AED (O^A), or abort (O^R), and the latter is set to t^{max}.
2. When step (1) is done for all dispatched volunteers, t^* and s^* are calculated according to Equations (3) and (4), respectively. Then, the survivability of the patient is calculated based on Equation (2).

Since one replication is a simulation of one possible patient outcome for the patient, several replications must be run for each case. The necessary number of replications was determined using the algorithm from Hoad et al. (2010) (see Section 6.3).

5.2. Travel time simulation

In the Netherlands, researchers have studied the modes of transport that volunteers have used for a project similar to the SMS lifesavers project (Zijlstra et al., 2015). While, to the best of our knowledge, no similar study has been done for Sweden, it is possible to simulate varying travel speeds based on historical data, reflecting various modes of transport.

Using tracked position data from a historical volunteer dispatch dataset, it is possible to determine an estimate, *TT*, of the historical travel time for each volunteer, from the initial location until reaching the patient. The Euclidian distance, *ED*, can be easily calculated based on the initial location of the volunteer and position of the patient, and thus, the Euclidian travel speed can be calculated as $ES = ED/TT$. If the volunteer picked up an AED, there are two Euclidian distances: (1) from the starting position to the location of the AED, and (2) from the AED to the patient; nevertheless, the travel speed can be calculated as mentioned, just using the sum of the two distances. Therefore, the tracked volunteers can be divided into two disjoint sets:

- CPR set: volunteers who went directly to the patient
- AED set: volunteers who picked up an AED on the way to the patient

For each set, it is possible to calculate travel speeds, giving ES^D as the set of Euclidian travel speeds calculated from the CPR set, and ES^A representing the set of Euclidian travel speeds calculated from the AED set. It may be noted that the speeds in the AED set implicitly accounts for the AED access time, that is, the time it takes to find and pick up the AED. The speeds are sorted according to the Euclidian distances, that is, for a set with k elements (Euclidian travel speeds), element 1 is the speed with the shortest corresponding distance, and element k is the speed with the longest distance.

In each simulation replication, three possibilities exist for dispatched volunteer j that result in different travel time calculations.

1. The volunteer's decision is D (O^D):
   a. Let the direct Euclidian distance to the patient be ED_j.
   b. From the set ES^D, find the N^Delements with Euclidian distances closest to ED_j, and randomly draw one of these speeds. This gives ES_j.
   c. Calculate $TT_j = ED_j/ES_j$.
2. The volunteer's decision is A (O^A):
   a. Let the Euclidian distance to the patient, via an AED, be ED_j.
   b. From the set ES^A, find the N^A elements with Euclidian distances closest to ED_j, and randomly draw one of these speeds. This gives ES_j.
   c. Calculate $TT_j = ED_j/ES_j$.
3. The volunteer's decision is R (O^R):
   a. Set TT_j to a big number (in this case, the volunteer would never reach the patient.).

6. Input data

To test and validate the model, we received anonymized historical data for dispatches of volunteers from the research group in charge of the SMS lifesavers project in Sweden (Ringh et al., 2015; Berglund et al., 2018). It included information on missions for each day from 2018-May-03 to 2018-September-10, consisting of one or more missions per day. The dataset contained also positions of patients, volunteers, and AEDs; time that the call center was notified; notification times of volunteers; and acceptance times and/or rejection times. The dataset also included

Global Navigation Satellite System (GNSS) based position tracking of the volunteers after dispatch. This data was complemented by information from a survey that was filled out by the volunteers who had been assigned a mission. It included questions about what they had done after they had received their task assignments. However, not all volunteers filled out the survey completely.

6.1. Travel times

We calculated estimated travel times, for use in the dispatch methods, for each volunteer based on the geographical location of patients, volunteers, and AEDs. $T_{O_j^A}$ and $T_{O_j^D}$ are based on the Euclidean distance between volunteer j and the patient ($T_{O_j^A}$ is the travel time via the AED that gives the shortest possible total path to the patient), and a travel speed of 2 m/s. Although previous studies indicate that pedestrian walking speed typically is slower, for example, 1.38 m/s (Khalemsky & Schwartz, 2017), we assume that volunteers will be running. Also, 2 m/s is the value incorporated in the dispatch system used in the SMS lifesavers project, and for comparative purposes, it is reasonable to use the same value here. $T_{O_j^R}$ can be set to a large number, since the volunteer will never reach the patient.

For the simulation, the set of Euclidian travel speeds for volunteers going directly to the patient (ES^D) had 867 elements, and going via an AED (ES^A) had 210 elements. To get the number of required samples, we took inspiration from the formula for sample size calculation (Daniel, 1995) with a confidence interval of 90 percent and an allowed margin of error of 10 percent, and bootstrap sampling (Hall, 1995). Therefore, N^D was set to 70 (with 35 distances lower than ED_j, and 35 distances higher than ED_j included in the set from which the new random travel speed was drawn, unless an equal number of data points on both sides were unavailable and then more data points from the other side were included, e.g., 10 distances lower and 60 distances higher), and N^A was set to 50.

6.2. Task compliance probabilities

By merging the mission data with the survey data, we could calculate the required probabilities, that is, probabilities of task compliance, noncompliance, and rejection. Compliance/noncompliance of volunteers were determined based on both the mission information and the surveys. We could extract the rate of abort directly from the mission data. Thus, the probabilities of aborting after accepting a task (picking up an AED, or going directly to the patient), complying with the instruction, and doing the alternative task other than the instructed one were calculated (below for task D). The probabilities of outcomes $O^A|D$, $O^D|D$, and $O^R|D$ were calculated as:

$$P(O^A|D) = count(O^A|D)/\left(count(O^A|D) + count(O^D|D) + count(O^R|D)\right) \quad (10)$$

$$P(O^D|D) = count(O^D|D)/\left(count(O^A|D) + count(O^D|D) + count(O^R|D)\right) \quad (11)$$

$$P(O^R|D) = count(O^R|D)/\left(count(O^A|D) + count(O^D|D) + count(O^R|D)\right) \quad (12)$$

Where we have:

1. $count(O^A|D)$: the number of volunteers that picked up an AED while they should have gone directly to the patient, that is, noncompliance with assignment.
2. $count(O^D|D)$: the number of volunteers that went directly to the patient as they were instructed to do so, that is, compliance with assignment.
3. $count(O^R|D)$: the number of volunteers that aborted their missions.

In the same way, we calculated probabilities of outcomes for when the volunteers were assigned to pick up an AED (task A), that is, $O^A|A$, $O^D|A$, and $O^R|A$.

The dataset consisted of 707 missions. In accordance with the formulas (10)–(12) and similar formulas for task A, the probabilities were calculated as:

$$P(O^D|D) = 0.659, P(O^A|D) = 0.048, P(O^R|D) = 0.293$$

$$P(O^D|A) = 0.348, P(O^A|A) = 0.352, P(O^R|A) = 0.300$$

It is noteworthy that the effect of task assignment A is very small, in terms of probability that a volunteer will indeed pickup an AED. In addition, regardless of the assigned task, the probabilities of rejection are roughly the same, indicating an independence between task assignment and rejection probability.

6.3. Determining the number of replications for the simulation

To determine the number of required replications for each case, we used the algorithm by Hoad et al. (2010), which is designed to handle the problem of premature convergence. Initially, three replications are run. The results of these replications are fed to the replication algorithm, which determines whether the precision criteria are met or not– without a premature convergence. If they are met, the algorithm terminates; otherwise, another simulation replication is performed, and the precision check is performed. This process repeats until a stable convergence is achieved. The precision criteria that we considered for our simulation are a 99 percent confidence interval ($\alpha = 0.01$) and allowed deviation from the mean by 10 percent.

7. Computational results

In this section, we present results from the implementation of the SePTAD method and the original method (analytical results) as well as the simulation results for both methods. Then, we compare the analytical and simulation results of both methods.

7.1. Analytical results

To investigate whether the SePTAD method contributes to improving the survival chance of OHCA patients, we tested the method on the dataset and compared it to the method currently used in the SMS lifesavers project (i.e., the original method). As described in Section 3, the project uses a static method with a rule block of A-A-D-A-A, where A means to pick up an AED and D to go directly to the patient, that repeats until all volunteers have received an assignment.

As the historical task assignments were available in the input data, we should have been able to compare the SePTAD method to them. However, when analyzing the input data, it became evident that the specified method was not always followed, meaning that the cutoff time, the upper bound for travel time of volunteers to be considered for dispatch, sometimes varied (i.e., the same value was not used for all cases). Consequently, instead of using the available historical task assignments, we implemented our own version of the original dispatch method used in the SMS lifesavers project. In this implementation we used exactly the same rule block as in the SMS lifesavers project (i.e., A-A-D-A-A) and considered one exact cutoff time, as described to us by researchers involved in the SMS lifesavers project. This implemented version means that volunteers with travel times longer than the cutoff time, who might have been given a task assignment in the historical data, would be excluded from task assignment in our implementation. Subsequently, after determining the task assignment for each volunteer using the rule block, we calculated the patient survival chance in the same way as for the SePTAD method (i.e., considering compliance, noncompliance, and abort probabilities). This way, it was possible to

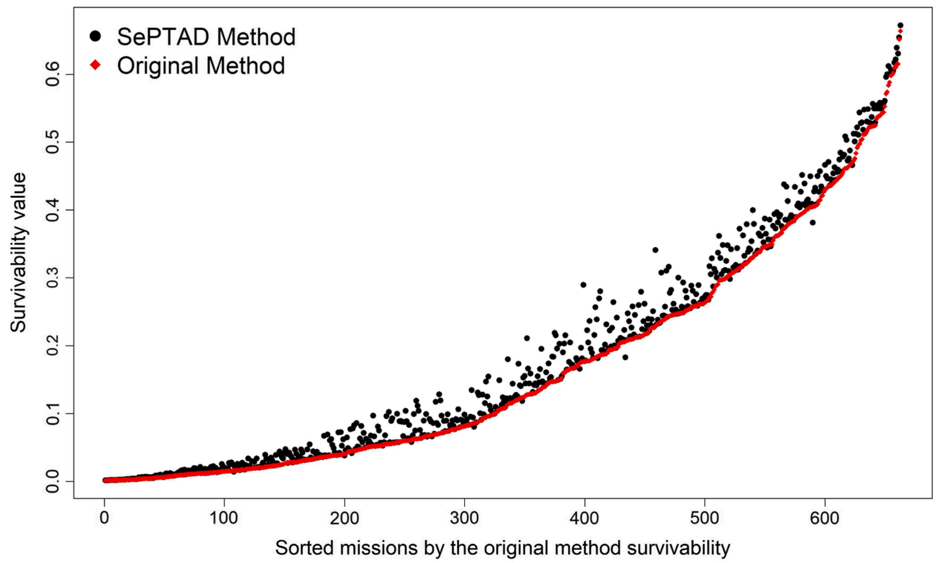

Fig. 1. Analytical patient survivability for the SePTAD method and the original method.

Table 1
The comparative results for survivability of the SePTAD method and the original method.

	Min	Q1	Mean	Median	Q3	Max	Standard Deviation
Difference in survivability	−0.024	0.002	0.015	0.008	0.022	0.113	0.018
SePTAD method	0.001	0.038	0.182	0.125	0.29	0.672	0.167
Original method	0.001	0.03	0.167	0.108	0.262	0.664	0.162

guarantee that a fair comparison could be made.

We then compared the results from using the SePTAD method to the results of the implementation of the original method. In the implementation of both the SePTAD method and the original method, we set the cutoff time to 15 min, and t^{max} and s^{max} to 15 min. While it might have been preferable to set t^{max} and s^{max} to the historical EMS arrival time, we lacked this data. Setting it to some expected EMS arrival time is another option, which we discuss as possible future research. The action of task assignment plus dispatch was made for a maximum of 10 volunteers in both methods.

Out of the 707 missions in the dataset, in 44 missions, no dispatch was made, because none of the volunteers responded to the notifications. For the remaining of 663 missions, the comparative results are presented in Fig. 1 and Table 1.

In Fig. 1, we illustrate the survivability values based on the survival function (2) for both the SePTAD method and the original method, sorted by an increasing survivability value for the original method. In 90 percent of the cases, the SePTAD method performs better compared to the original method. In 4 percent of the cases, the original method performs better than the SePTAD method, and in the remaining 6 percent of the cases, both methods perform equally well. When the SePTAD method outperforms the original method, it results in at most a 0.113 higher survivability than for the original method. Whereas, when the original method performs better than the SePTAD method, the best survivability achieved by the original method is 0.024 higher. As indicated in Table 1, the SePTAD method on average gets a 0.015 higher survivability than the original method.

We present statistics from the results of the two methods in Table 1 (rows SePTAD method and Original method). To obtain the results for the row "Difference in survivability of methods", we first calculated the difference in survivability obtained from each of the methods for each case, and then calculated the statistic measures over all of those differences (e.g., mean difference in survivability over all cases). While the values for minimum, maximum, and standard deviation do not differ significantly between the two methods, values for first quantile (25 percent of the cases have a survivability lower than Q1), mean, median, and third quantile (25 percent of the cases have a survivability higher than Q3) clearly differ. To investigate whether the two methods are statistically significantly different or not, we used the sign test for matched pairs (Moore & McCabe, 1999) on the results. The output of the test indicated that, with a confidence interval of 95 percent, the median of the results of the SePTAD method, 0.125, is statistically significantly higher than the median of the results of the original method, 0.107; P-value $<$ 2.2e-16, 95% confidence interval: [0.01, 0.013].

As already mentioned, to the best of our knowledge, no documented and published data on time between volunteer arrival and start of CPR or defibrillation (i.e., setup time) or AED pickup time is available. However, to examine the effect of considering these times in the outcome of both dispatch methods, we ran tests for both the SePTAD method and the original method, including a delay of one minute, to accommodate for picking up an AED and setting it up. We added this constant value to the travel times of all volunteers via AEDs. As expected, when comparing the results with and without this delay, it is evident that the survival chance in general decreases when the AED pickup time is included, but it has an insignificant effect on the difference between the two methods. Even if the result is trivial, it highlights the importance of the AED pickup time and the setup time, and how they can negatively affect the patient survival chance.

7.2. Simulation results

As described in Section 5, we used simulation to evaluate the reliability of results. For each case, we extracted descriptive statistics for the results of the simulation, such as mean, median, and variance, and compared them to the analytical results of the two methods. In Table 2, we present comparative results from the simulation using the SePTAD method and the original method.

Comparing the results presented in Table 2 and Table 1, it is evident

Table 2
The comparative simulated results between the SePTAD method and the original method.

	Min	Q1	Mean	Median	Q3	Max	Standard Deviation
Difference in survivability	−0.035	−0.001	0.007	0.005	0.013	0.09	0.014
SePTAD method	0.001	0.046	0.14	0.116	0.197	0.585	0.114
Original method	0.001	0.042	0.132	0.113	0.184	0.57	0.107

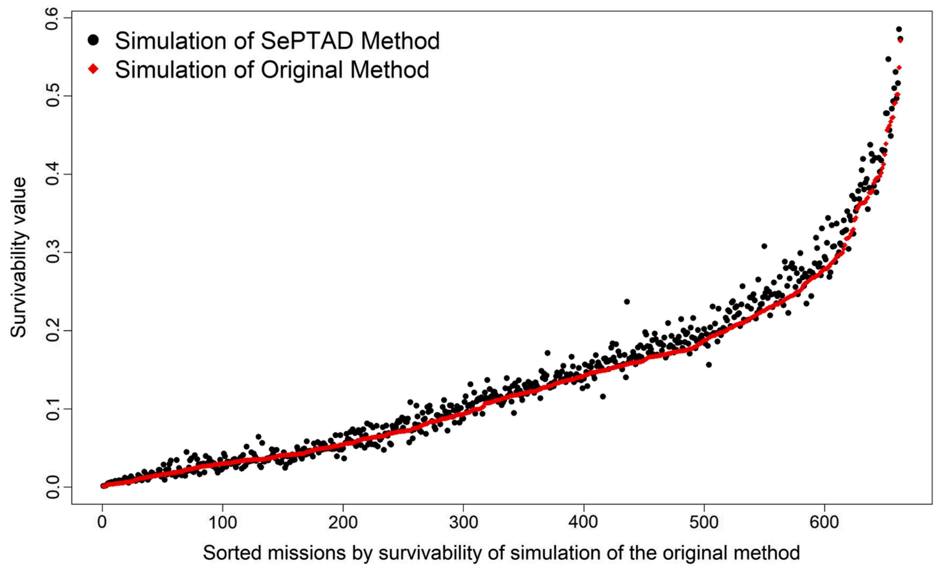

Fig. 2. Simulated patient survivability for the SePTAD method and the original method.

that all measures for both methods and the difference in their survivability have lower values in the simulation. Furthermore, the difference between the two methods has decreased. For instance, the mean of difference in survivability has decreased by 0.008 (from 0.015 to 0.007 for analytical and simulation results, respectively). The percentage of cases for which the SePTAD method has performed better than the original method during the simulation is 71. This is a drop of 19 percentage units compared to the analytical results. In Fig. 2, we demonstrate the results of the simulation for both methods, sorted increasingly based on survivability values of the original method.

To check whether the simulation results of the two methods are statistically significantly different or not, we used the sign test for matched pairs for these results as well. With a confidence interval of 95 percent, the median of the results of simulation of the SePTAD method, 0.116, is statistically significantly higher than the median of the results of the original method, 0.113; P-value $<$ 2.2e-16, 95% confidence interval: [0.005, 0.007].

To investigate how the analytical and simulation results relate to each other, we calculated the correlation coefficient for each pair of results (i.e., the SePTAD method vs. its simulation, and the original method vs. its simulation). This coefficient for both pairs was about 0.97, indicating a positive and strong relationship between the results of each method and its simulation.

8. Sensitivity analysis

In our analysis, we have set values for the EMS arrival time (t^{max} and s^{max}) as well as the cutoff time to 15 min and have used a single set of probabilities (see Section 7.1). We have also used Euclidian distances rather than route distances and have also assumed that no bystander is present at the time of dispatches. In this section, we conduct sensitivity analysis to see how changes in these values and assumptions affect the results.

8.1. EMS arrival time

To investigate the effect of EMS arrival time on the patients' survivability obtained from the two methods, we consider different values for t^{max} and s^{max}: {3, 5, 8, 10, 12, 15, 18, 20, 30, 40, 50}. In Table 3 and Fig. 3, we present descriptive statistics for each of the tested EMS arrival times. As can be seen in Fig. 3, both methods behave similarly. However, looking at the difference in survivability between the two methods in Table 3, the SePTAD method obtains better survival chances than the original method regardless of EMS arrival time, with the best values obtained for arrival times of 8–12 min. Also, when the SePTAD method performs better than the original method, a higher survival difference is obtained compared to when the original method outperforms the SePTAD method (see columns "Min" and "Max").

The results in Table 3 are obtained when the cutoff time is set to 15 min. To check whether different cutoff times will result in different outcomes, we run the methods with cutoff times of 10 and 20 min as well. However, for EMS arrival times above 18 min, almost no effect from EMS can be seen. Thus, we compare the results of different cutoff times only up to an EMS arrival time of 18 min. In Fig. 4, we show the average difference in survivability for different cutoff times.

In Fig. 4, it is evident that a cutoff time of 10 min results in a larger mean difference in survivability than the other two cutoff times. With the increase in cutoff time, the difference between the two methods seems to decrease. A possible explanation might be that with a cutoff time of 10 min, the pool of volunteers eligible for task assignment is smaller than that with a cutoff time of 15 or 20 min. Thus, using a smarter dispatch method becomes more important, since the number of resources is smaller. Regarding the survivability pattern for each of the methods (Fig. 3) and the difference in survivability (Fig. 4) with respect to different EMS arrival times, we note the following:

- When EMS have a very short arrival time (i.e., three minutes), the dispatch method does not matter. With the early arrival of EMS, the

Table 3
Descriptive statistics for difference in survivability between the SePTAD method and the original method for different EMS arrival times and a cutoff time of 15 min.

EMS arrival time (minute)	Min	Q1	Mean	Median	Q3	Max	Standard deviation
3	−0.003	0.000	0.007	0.000	0.005	0.069	0.014
5	−0.004	0.000	0.016	0.003	0.023	0.104	0.024
8	−0.025	0.000	0.019	0.008	0.030	0.111	0.024
10	−0.011	0.000	0.017	0.009	0.028	0.119	0.021
12	−0.018	0.001	0.016	0.009	0.025	0.115	0.019
15	−0.024	0.002	0.015	0.008	0.022	0.113	0.018
18	−0.022	0.001	0.014	0.007	0.021	0.113	0.018
20	−0.030	0.001	0.014	0.007	0.020	0.113	0.018
30	−0.029	0.000	0.013	0.006	0.019	0.114	0.018
40	−0.029	0.000	0.013	0.006	0.018	0.114	0.018
50	−0.029	0.000	0.013	0.005	0.018	0.114	0.018

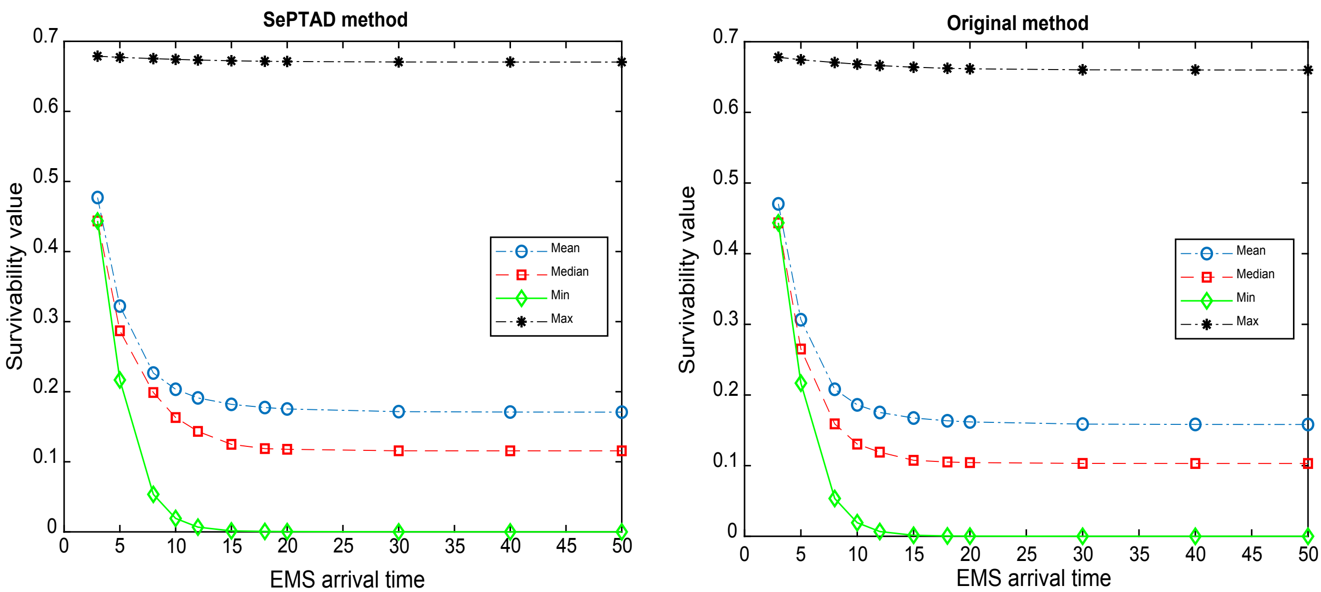

Fig. 3. Survivability of the SePTAD method (left) and the original method (right) for different EMS arrival times and a cutoff time of 15 min.

patient quickly receives both CPR and defibrillation, and the survivability of the patient is therefore not dependent on the volunteers.

- For longer EMS arrival times (i.e., 15 min and more), which for example can happen in rural or suburban areas, the difference between the two methods decreases. This may be due to the fact that the original method always dispatches the first two volunteers to fetch an AED. Then, the SePTAD method has a good chance of improving the survivability, if one of these volunteers can be dispatched directly to the patient to start CPR, and then the AED is brought by an ambulance. The chance for this, decreases when the EMS arrival time increases.

8.2. Probabilities

To obtain the results in Section 7, we used a fixed set of conditional probabilities. In this section, we test both methods with different sets of probabilities to see how the results will differ with respect to these probabilities.

We start by investigating the full compliance case, that is, all volunteers will do exactly as they are instructed without rejecting or doing the alternative task, $P(O^A|A) = P(O^D|D) = 1$. As can be seen in Table 4, the results for full compliance for both methods are better than when both noncompliance and rejection probabilities exist. The improvement for the SePTAD method is larger than for the original method though, which shows that a dynamic dispatching method can be even more beneficial under full compliance.

To perform the analysis on partial compliance, we keep one group of conditional probabilities (i.e., conditioned on task A or D) fixed and change the compliance and noncompliance probabilities for the other group. We do not change the probabilities for reject because we are interested in knowing how the reduction of noncompliance probabilities can affect the survivability. Through education campaigns for instance, it might be possible to motivate volunteers to be more compliant with their task assignments, but it might be more difficult to convince them not to reject a mission. In Fig. 5 we show the mean survivability for each set of probabilities conditioned on task A (i.e., picking up an AED), while the probabilities conditioned on task D are kept unchanged (e.g., at $P(O^D|D) = 0.659$). In this figure, probabilities are indicated for instance as PAA0.65 that is equivalent to $P(O^A|A) = 0.65$, and each data point shows one combination of probabilities (i.e., compliance, noncompliance, and reject for task A, in that order of appearance).

As we can see from Fig. 5, with the increase of compliance probability for task A, the survivability for both methods increases. However, the improvement for the SePTAD method is larger than for the original method.

The noncompliance probability for task D is already at a very low value (0.048) so to further increase compliance probability for task D is not especially interesting.

8.3. Survival function

The SePTAD method uses the survival function of Matinrad et al.

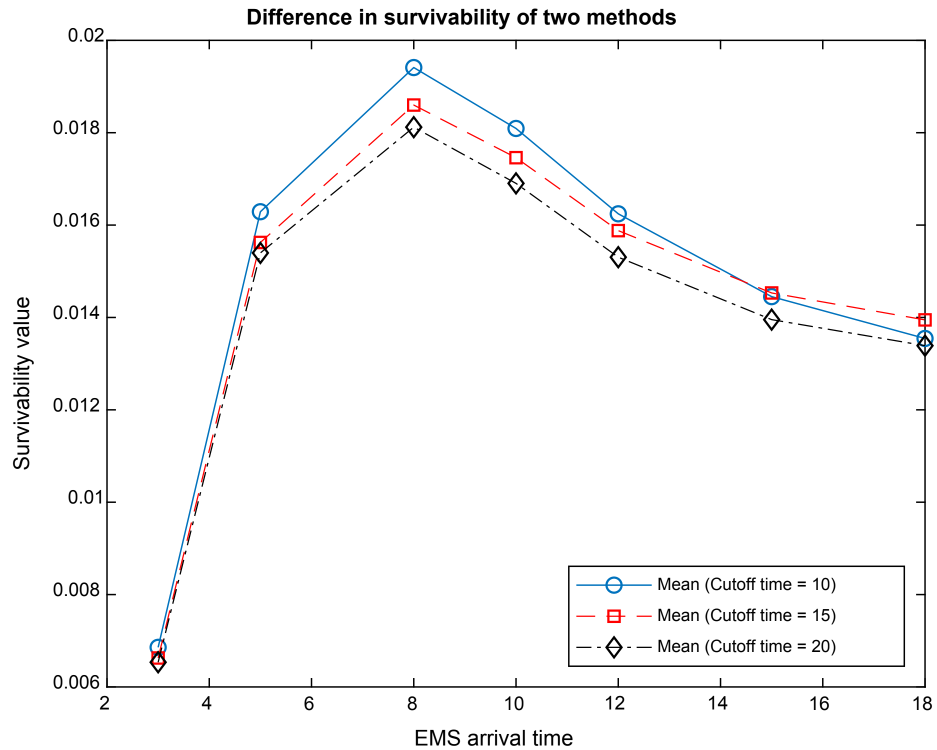

Fig. 4. Mean difference in survivability between the SePTAD method and the original method for different cutoff times and EMS arrival times.

Table 4
Survivability for the SePTAD method and the original method for the full compliance case and the original case (Baseline).

	Full compliance			Baseline		
	SePTAD	Original	Diff**	SePTAD	Original	Diff**
Min	0.001	0.001	−0.095	0.001	0.001	−0.024
Q1	0.058	0.022	0	0.038	0.03	0.002
Mean	0.249	0.208	0.042	0.182	0.167	0.015
Median	0.201	0.123	0.006	0.125	0.108	0.008
Q3	0.417	0.362	0.058	0.29	0.262	0.022
Max	0.733	0.733	0.349	0.672	0.664	0.113
Std*	0.208	0.208	0.068	0.167	0.162	0.018

* Standard deviation; ** Difference in survivability of methods

(2019). To investigate the effect of survival function choice on the outcome of both methods, we use two other survival functions from the literature by Larsen et al. (1993) and Valenzuela et al. (1997) and present the results of these tests in Table 5. The reason for choosing these two functions is that both of them calculate the survival chance using the same parameters as in Matinrad et al. (2019).

As we can see in Table 5, the survival function from Valenzuela et al. (1997) gives slightly higher survival chances than the ones in Matinrad et al. (2019), while Larsen et al. (1993) gives values close to Matinrad et al. (2019) but overall lower. Nevertheless, it does not seem to matter much which survival function is used in regards of the difference between the two methods; the SePTAD method always gives a better survivability than the original method.

8.4. Travel distance

As shown in previous studies, such as Deakin et al. (2018) and Fan et al. (2020), the walking distances might be 1.3–2.4 times longer than the Euclidian distances, which is used in both the SePTAD method and the original method. Obstacles such as terrain or water (Smida et al., 2020), which would mean longer travel times for volunteers, might exist. Taking this into account may affect the task allocation, wherefore we examine the effect of these types of longer route distances. In the analytical method, we multiply the volunteers' Euclidian distances (both directly and via an AED) by a factor within the range of $[1.3, 2.4]$ (see Table 6). As we can see in Table 6, by increasing the distance factor, the difference between the two methods decreases, but the SePTAD method still obtains better results than the original method. Increasing the distance factor means that the volunteers have longer travel times, and consequently, fewer volunteers would be below the cutoff time. Therefore, the number of cases in which volunteers eligible for task assignment exist reduces from 663 cases in the baseline scenario (i.e., the distance factor equals to one) to 527 cases for which a distance factor of 2.4 is considered. This also means that those volunteers who are dispatched have longer response times that are closer to the cutoff time. With longer response times, the impact of the volunteers' responses becomes smaller, and therefore, the difference between the two methods decreases.

8.5. Travel time model

As already noted, the survival chance of the patient, as well as the difference between the two methods, decreased significantly when simulating the outcome, as compared to the analytical results, as well as when a travel distance factor was included. One possible reason for this is the rough travel time estimation used when making the dispatch decisions with the SePTAD method. In order to investigate the effect of the travel time model when making dispatch decisions, we simply assume that the travel time in the simulation will be exactly the same as in the analytical model. Then we compare the analytical and the simulated results.

As can be seen in Table 7, for both dispatch methods, the analytical and the simulated results are very similar (both methods and their respective simulations have a correlation coefficient of 0.99). This means that if it is possible to find a better travel time model, which can be used when making the dispatch decisions, it should be possible to achieve the improvement given by the analytical results. Such a travel

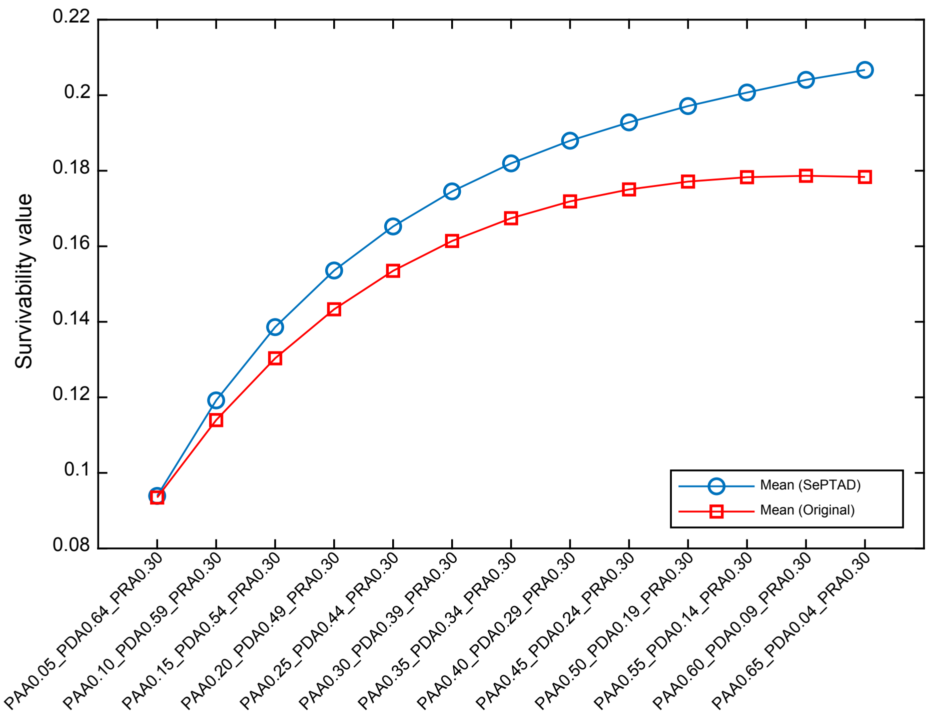

Fig. 5. Mean survivability for the SePTAD method and the original method with changing conditional probabilities for task A.

Table 5
Survivability of the SePTAD method and the original method with different survival functions.

	Larsen et al. (1993)			Valenzuela et al. (1997)			Matinrad et al. (2019)		
	SePTAD	Original	Diff**	SePTAD	Original	Diff**	SePTAD	Original	Diff**
Min	0	0	−0.007	0.032	0.032	−0.013	0.001	0.001	−0.024
Q1	0.043	0.016	0.001	0.091	0.084	0.002	0.038	0.03	0.002
Mean	0.128	0.117	0.011	0.193	0.183	0.011	0.182	0.167	0.015
Median	0.128	0.116	0.005	0.178	0.167	0.007	0.125	0.108	0.008
Q3	0.203	0.195	0.013	0.276	0.264	0.016	0.29	0.262	0.022
Max	0.314	0.312	0.089	0.485	0.479	0.061	0.672	0.664	0.113
Std*	0.092	0.094	0.015	0.112	0.110	0.011	0.167	0.162	0.018

* Standard deviation; ** Difference in survivability of methods

Table 6
Descriptive statistics for the difference in survivability between the SePTAD method and the original method for different distance factors.

Distance factor	Min	Q1	Mean	Median	Q3	Max	Standard deviation
1 (Baseline)	−0.024	0.002	0.015	0.008	0.022	0.113	0.018
1.3	−0.017	0.001	0.012	0.006	0.018	0.109	0.016
1.6	−0.022	0.000	0.011	0.005	0.015	0.089	0.015
1.9	−0.017	0.000	0.010	0.004	0.013	0.092	0.015
2.1	−0.011	0.000	0.010	0.003	0.012	0.080	0.014
2.4	−0.011	0.000	0.009	0.003	0.012	0.072	0.014

Table 7
Analytical and simulated survivability for both dispatch methods.

	SePTAD method			Original method		
	Analytical	Simulation	Diff**	Analytical	Simulation	Diff**
Min	0.001	0.001	−0.050	0.001	0.001	−0.037
Q1	0.038	0.038	−0.002	0.031	0.031	−0.002
Mean	0.182	0.182	−8.95E-05	0.167	0.168	−0.001
Median	0.125	0.124	3.128E-05	0.108	0.109	−5.3E-05
Q3	0.289	0.295	0.002	0.262	0.267	0.002
Max	0.672	0.678	0.041	0.664	0.666	0.03
Std*	0.167	0.168	0.007	0.162	0.162	0.007

* Standard deviation; ** Difference in survivability between analytical and simulated results

time model could take into account for example the road network as well as buildings and other infrastructures including possible barriers.

8.6. Bystander CPR

When deciding the task assignment for volunteers, we assumed that no bystander starts performing CPR. However, as already noted, in about 48 percent of OHCA cases, CPR is started by bystanders (Ringh et al., 2015). To study the effect of the presence of bystanders starting CPR prior to the arrival of volunteers and/or EMS, and how it would have affected the outcome of both methods if we considered a bystander in the methods when making the task assignment, we includ a dummy volunteer in each tested case. This dummy volunteer, representing a bystander, performs CPR with a probability of 0.48 and does nothing with a probability of 0.52. We also consider a fixed CPR start time of one minute for the dummy volunteer, as no data on the potential start time of bystander CPR exists in our data. With these assumptions, we ran both the SePTAD method and the original method to get new task assignments, followed by a simulation evaluation. In each simulation replication we randomly generated a bystander with a probability of 0.48. Moreover, data on start time of bystander CPR in literature is insufficient. Therefore, using a uniform distribution, we randomly generated a start time, assuming that it has a lower bound of 30 s and an upper bound equal to the direct travel time of the closest volunteer. We decided on this range so that it accommodates both bystanders who are trained in CPR as well as those who potentially have difficulty following a dispatcher's instructions when performing CPR. The results of these tests can be seen in Table 8.

Comparing the analytical results for both methods in Table 8 and Table 1, considering a potential bystander results in higher survival chance for the patient, as expected. We can see from Table 8 that the SePTAD method both analytically and in the simulated results performs better than the original method. Comparing the simulated results with the analytical results for each method, we can see that including a dummy volunteer at the time of task assignment leads to an overestimation of the survival chance, since the analytical results give higher values than the simulated. As we can see from the last two rows in Table 8, the advantage of the SePTAD method over the original method is almost identical.

9. Discussion

When an OCHA case is reported to the call center, the SMS lifesavers system is activated to notify the volunteers and dispatch a set of available ones. The number of available volunteers varies, and the system can work with any available number of volunteers. Of course, in some cases, no volunteers might be available at all. However, the goal with projects such as SMS lifesavers is helping the main emergency response system with achieving better survivability for patients, and not replacing the main system. On the other hand, it might be argued that dispatch of many volunteers to an OHCA case can be problematic on the scene of the event. This is handled by restricting the number of volunteers that the first notification is sent to, and because of the compliance uncertainties (including possible mission aborts), in practice the number of volunteers at the event site seldom becomes very large.

Some points regarding AED and OHCA cases are worth noting. While each OHCA case would require one working AED, more than one volunteer can be dispatched to pick up specific AEDs, or even the same AED. Therefore, in a hypothetical scenario, more than one AED can be brought to the patient, or a volunteer might arrive to an AED site from where the AED has already been taken. However, because of the uncertainties associated with compliance of volunteers, it is not possible to know for certain whether any AED will reach the patient, which is why multiple AED assignments are made, and why it is possible that two volunteers get assigned to the same AED.

Detailed analytical results of the SePTAD method show that in 79 percent of dispatches, send to AED (A) is selected. There are multiple reasons that can lead to this choice of task assignment. First, when sending to AED, the CPR time will be set equal to the AED time, that is $s^* = t^*$, since the volunteer bringing the AED also can start CPR. Second, the probabilities state that even if dispatched to AED, the chance is almost as high that the volunteer will go directly to patient instead. Thus, more volunteers must be sent to AEDs in order to increase the final probability of AED delivery.

When comparing the simulation and analytical results, we observe a drop in performance dominance of the SePTAD method in simulation results, but in most cases the SePTAD method performs better. In the best case, this has led to a survivability increase of 0.09 compared to the original method, which can result in potential life savings.

It is a relevant question whether the use of the SePTAD method instead of the original method would be meaningful in reality, when the calculated improvement in survivability seems rather small (see Table 1 and Table 2). If we consider the mean of difference in survivability (see Table 1), the additional number of people that could be expected to survive an OHCA, using the SePTAD method instead of the original method, would be 10, for the 663 studied cases. Given that the 663 cases were for a period of about four months, this would translate to 30 more saved lives per year in Sweden using a non-static dispatch method. Calculating the same numbers for simulated results (see Table 2), this number would be 5 for the 663 studied cases and period of almost four months, which corresponds to 15 more saved lives per year in Sweden using a non-static method. However, these numbers are as estimated by the survival function (2). Thus, it does not prove that it would improve the survivability for real patients, if implemented in the ongoing SMS lifesavers project. In order to test that, a randomized trial would have to be performed, with volunteers being dispatched to real cases using the original method in 50 percent of the cases and the SePTAD method in the others. However, since the survival function is developed to estimate OHCA survivability, and the improvement occurs, it is highly likely that the SePTAD method would improve the average survival chance also in a practical implementation. Moreover, as we have excluded potential initiation of CPR by bystanders from the model and task assignment methods, the analytical results obtained from both dispatch methods can to some extent be considered as worst-case scenarios for the patients'

Table 8
Analytical and simulated survivability for both dispatch methods considering bystanders.

		Min	Q1	Mean	Median	Q3	Max	Standard deviation
SePTAD method	Analytical	0.070	0.115	0.259	0.231	0.368	0.674	0.154
	Simulation	0.020	0.104	0.252	0.218	0.374	0.673	0.164
	Diff*	−0.054	−0.007	0.007	0.005	0.020	0.063	0.020
Original method	Analytical	0.070	0.111	0.246	0.214	0.352	0.666	0.149
	Simulation	0.019	0.099	0.240	0.207	0.357	0.679	0.159
	Diff*	−0.062	−0.007	0.006	0.005	0.019	0.063	0.019
AnalDiff**		−0.030	0.002	0.013	0.008	0.019	0.095	0.016
SimDiff***		−0.053	0.001	0.013	0.009	0.020	0.103	0.020

* Difference in survivability between analytical and simulated results; ** Difference between both methods in analytical survivability; *** Difference between both methods in simulated survivability

survival chance.

10. Conclusion and future research

To investigate whether dynamic modeling of dispatch of volunteers can improve the survivability of OHCA patients, we develop a sequential, probabilistic method. We incorporate a survivability function and consider uncertainty in volunteer task compliance in this method. Compared to the dispatch method used in the SMS lifesavers project in Sweden, we show that the new method performs better in most cases. Considering the relatively small difference when the method performs worse, and the significant improvement when the method performs better, we can conclude that using a non-static dispatch method most likely would provide OHCA patients a better overall survival chance. The proposed method can also be used as a component in emergency resource management systems to dynamically handle volunteers.

In the proposed method we consider one type of uncertainty, associated with the task compliance of the volunteers. However, more uncertain elements related to this problem exist. In this paper, we consider some of those uncertain elements, such as travel times of volunteers, pickup time for AEDs, functionality of AEDs, and AEDs availability, as deterministic. Thus, a step forward in continuation of this study can be to include these uncertainties in the dispatch modeling. Also, if enough data exists, the performance of individual volunteers in previous missions (i.e., the likelihood of each volunteer complying with the assigned task over time and different cases), as well as their capabilities, can be measured, and they can be ranked accordingly. Consideration of these rankings in the task assignment and dispatch decisions can then be another future step.

It is reasonable to consider that there is correlation between the distance of a volunteer to the patient and the probability to abort. Consequently, besides the types of the task assigned to volunteers, the distances can have an impact on the probabilities of compliance, noncompliance, and abort. Therefore, modeling of compliance, noncompliance, and abort probabilities depending on the distances of volunteers and patients and volunteers via an AED, in addition to the types of assigned task, can be another future step.

To include estimates of the EMS arrival time in the dispatch method, for example based on historical response or ambulance station locations, or even real time ambulance dispatches is another possibility for further improvement of the dispatch methods. It is important to note though that these estimates also are uncertain (especially the ones based on historical data).

We show that some of the possible benefits of having an optimized dispatch method is lost if the real travel times for the volunteers differ from the estimates used when making the dispatch decision. Thus, the travel time estimation should be improved, if possible. One way to do this is to include more information (e.g. about the road network, the volunteer's position and altitude, the possibility to use a vehicle, barriers or obstacles, etc.) in the travel time modeling.

There is a possibility that more than one OHCA case might occur around the same time and geographical location. The way volunteers would be dispatched to these cases would be on a first-come-first-served base; volunteers would be notified and dispatched to the first case that arrived at the call center, and then possibly to the second case. Here, there is room for further research, on how to dispatch volunteers when there are multiple active cases.

CRediT authorship contribution statement

Niki Matinrad: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Tobias Andersson Granberg:** Conceptualization, Funding acquisition, Methodology, Resources, Supervision, Validation, Writing - original draft, Writing - review & editing. **Vangelis Angelakis:** Conceptualization, Methodology, Resources, Writing - original draft, Writing - review & editing.

Data availability statement

The authors do not have permission to share the data.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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