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A bayesian approach for the continuous monitoring of the prediction of the physiological evolution of a crisis victim: A decision support system

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ABSTRACT

Catastrophic events like earthquakes demand innovative tools for crisis management. Mathematical modeling and decision support systems (DSSs) have proved crucial for understanding, predicting and mitigating disaster impact. The quantification of complex phenomena through probabilistic models, to estimate the likelihood of events, provides actionable insights that are essential for disaster risk reduction (DRR).

The present work stems from research conducted within the framework of the Search & Rescue (S&R) project (H2020-SU-SEC-2019), in particular from the development of the PHYSIO DSS module, the medical component of the S&R Decision Support System (DSS). The PHYSIO DSS focuses on predicting the physiological evolution of crisis victims: using a Bayesian approach, it incorporates real-time field observations to forecast patient conditions. This enables the prediction of the evolution of physiological compensation, allowing efficient resource allocation and timely interventions. By providing real-time insights into victim severity, PHYSIO DSS empowers medical personnel to prioritize treatment, potentially saving lives. Its adaptability allows integration into different platforms, from crisis management systems to apps to personal health devices.

This tool has the potential to substantially enhance emergency response capability and overall disaster resilience by offering real-time, data-driven decision support.

1. Introduction

Earthquakes, landslides, floods, terrorist attacks, toxic chemical spills, explosions, etc. are events which lead to mass casualty incidents (MCI). A mass casualty incident is an event that generates a sufficiently large number of casualties so to challenge the available organizational and medical resources, or their management systems, or to make them insufficient to adequately meet the medical needs of the affected population [1].

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During MCIs, various triaging systems (SORT [2], SIEVE [3], START [4], JUMP START [5]) are used to categorize injured persons. While these systems are simple, they can lead to static over- or under-triaging [6]. Triage should be dynamic, as patients' conditions can change. Moreover, treatment and evacuation must consider both the number of victims and available resources (treatments, transports, medical personnel). A more sophisticated system, allowing for consideration of these factors, could improve crisis response. Pre-hospital treatment and immediate evacuation of the most injured are also crucial. Continuous monitoring of victims on-site, providing insight into the occurrence and severity of possible lesions and about hidden physiological impairment, is essential for real-time decision-making. Mathematical modeling and decision support systems (DSS) can aid in understanding, predicting, and mitigating disaster impacts. Probabilistic models can estimate survival probabilities and inform disaster risk reduction (DRR).

Most DSSs in MCIs focus on patient-to-hospital allocation (driving times to the nearest hospitals, the trauma service level of each hospital, the location of hospitals with respect to the incident site, hospital capacity [7]). They do not address patient health monitoring. DSSs addressed to patient care are the Clinical Decision Support Systems (CDSSs) mainly used in clinical settings to aid in treatment suggestions, information alerts, and medication interaction detection. They are particularly useful for cardiovascular disease management [8]. A recent Recently, a CDSS has been proposed to determine the severity of Chronic Obstructive Pulmonary Disease (COPD) in chemical injury victims [9], demonstrating its value in diagnosis and assessment.

In the field of disaster management, we found that the use of mobile applications for alerting and informing the population has become a common feature today. In a recent contribution, Syukron et al. [10] conducted a study on the most common available mobile applications (45 disaster apps) to understand their key features and applications. The key features of these apps can be grouped into four categories: 1) “Preparation”, which includes tutorials, forecasting, and warnings of potential disasters; 2) “Response”, providing real-time alerts or tracking of disasters (some applications even displaying a map of the affected zone); 3) “Recovery”, providing a specific section for collecting updates on the disaster; 4) “Mitigation”, offering behavioral recommendations and safe zone information. None of the analyzed apps were designed to monitor patient health trajectories or predict physiological outcomes for a more efficient victim prioritization or to optimize healthcare resource allocation during potential shortages.

Decision Support Systems (DSS) for predicting the evolution of a crisis victim's physiological status were first introduced in Refs. [11,12]. The mathematical model used describes deterministically the patient's evolution in terms of piecewise-linear functions in ten physiological dimensions. Borri et al. [12] presented an integrated platform for simulating trauma incidents using interacting deterministic mathematical models. The platform generates incident scenarios, models affected individuals' physiological changes with treatment effects and helps allocate resources. It was founded on European funded projects IMPRESS [13] and PULSE [14]. This work was further developed in the Search & Rescue project (https://search-and-rescue.eu/), leading to the PHYSIO DSS (PHYSIOlogical evolution of the victim Decision Support System) tool described here.

The PHYSIO DSS offers a probabilistic version, using real-time information to predict victim evolution with a completely asynchronous Bayesian approach. It calculates probability distributions of 10 Physiological State Variables' (PSVs), representing the victim's health condition. The final output is the a-posteriori distribution of the Expected Time to Death (ETD), supporting on-site decision-making related to victim prioritization and resource allocation. Despite the complex and often ineffective nature of disaster risk reduction (DRR) policies [15,16], it is indeed of paramount importance to prioritize actions and strategies based on available information [17].

Several studies have employed Bayesian approaches to enhance disaster risk management [18–20]. The work of Pellegrino et al. [18] investigates the connections between supply chain disruptions, risk mitigation strategies, and firm performance using a specific methodology that combines interpretive structural modeling and Bayesian networks. The work of Rahman et al. [19], instead, uses a Bayesian procedures to predict the probability of future disaster occurrences and the magnitude of their impact based on past data. Wu et al. [20] proposes a method combining Bayesian networks and geographic information systems to assess flood disaster risk. This method captures the relationships among the different factors impacting flood disaster and quantifies uncertainty using both data and knowledge-based sources.

Several approaches can help the decision-making process in case of disasters. Spatial Decision Support Systems (SDSSs) are designed for selecting optimum locations for response teams, for designing evacuation routes or for allocating evacuees to shelters [21–23]. In this context Multi-Criteria Decision Analysis (MCDA) [24–26] or the Structured-Decision making (SDM) [27] have been developed for driving decision-making by means of the evaluation of different alternatives or scenarios according to multiple criteria. These approaches integrate the outputs of multiple models, compare actions and scenarios and support decision-making. The PHYSIO component fits into this framework with the potential of providing, if appropriately connected, information on specific aspects of the severity of the victim and its evolution over time. Its output could serve as a target in a multi-object cost function to be minimized (individuals with lower average expected time to death should be assisted or evacuated first to minimize the losses). The ETD can also assist physicians in determining the optimal allocation of healthcare resources to a victim by exploring various treatment scenarios and computing the corresponding expected time to death for each.

Within the context of Disaster Risk Management, the PHYSIO component supports the development of strategies to mitigate existing risks and manage residual hazards, thereby enhancing resilience and reducing disaster losses. Specifically designed for tactical decision-making, the PHYSIO aids in field operations such as ambulance deployment, treatment allocation, team management, triage, and victim prioritization. Predicting how an impairment might progress in an individual can inform personalized treatment plans, interventions, and preventive strategies. This information is valuable for both medical and disaster risk reduction professionals. These functionalities were integrated into the S&R Decision Support System and tested in two table-tops and in a real-world use case.

The next section describes the methodology, the functions and algorithms constituting the architecture of the PHYSIO DSS, while the Results section shows the results obtained by simulating the occurrence of an earthquake with its associated victims.

2. Methods

The main purpose of the PHYSIO DSS is to provide a victim prioritization and a better resource allocation based on an estimation of the expected time to death (ETD) of each victim of the disaster, as time passes, computed from the probability distributions of 10 Physiological State Variables (PSVs) and from the associated probability distributions of the PSVs' rates of change. The present section aims at describing the functioning of the PHYSIO DSS, its internal algorithms and the way it exploits real-time information (health parameters values and treatment administration) for the prediction of the evolution of the physiological status (described by the 10 PSV distributions) of the victims in a completely asynchronous Bayesian approach, i.e. through the computations of "a-posteriori" probability distributions derived by combining "a-priori" distributions and observed values of health parameters.

A Bayesian approach employs probability distributions to represent varying degrees of certainty about events or parameters. Bayes' theorem enables the calculation of these distributions by incorporating new data with existing prior knowledge (a-priori probability distributions). The resulting posterior distributions are used to make inferences about the parameters of interest. In this scenario, for each disaster victim an initial estimate of the potential severity of their physiological condition is made (prior distribution). Then, new information gathered from on-site health assessments is used to refine this initial estimate in a continuous process, resulting in an updated assessment of the physiological status likelihood. Changes in PSV distributions over time are reflected in changes in ETD distributions. All the information relating to a victim is collected inside a PIE, which is a long string containing the necessary elements to describe where a victim is positioned in the Physiological State Variables' (PSVs) space. Table 1 reports a formal description of the PIE, PSVs and of the Rates of change of the PSVs. The use of the probability distributions to describe the victim's status allows to formalize the uncertainty and randomness proper of a real situation. The initial a-priori distribution on the victim's "physiological status" is a collection of 10 probability distributions, one for each of the 10 PSVs (expressing the level of compensation for each of 10 relevant physiological systems), reflecting the most likely values of the PSVs according to the very first (limited) available information coming from the field at the very initial phase of the rescue operations (as the position of the victim with respect to the event location). This collection of probability distributions is then subsequently updated, through a Bayesian approach, whenever new information on the victim's health status becomes available (as for example measurements of respiratory rate, heart rate, blood pressure etc …). In addition to measuring victim vital parameters, new information may refer to other indicators as the passage of time or the possible application of therapies/treatments: whenever any information about the victim is made available at any time and in any order and number, it is used to improve knowledge of the victim, updating the a-priori probability distributions to obtain an estimate of the a-posterior PSV distributions describing the new (updated) physiological state in a probabilistic way.

2.1. Overview of the PHYSIO DSS architecture

The PHYSIO DSS has been developed as part of the overall Decision Support System of the Search & Rescue project and has been provided as web-services. Fig. 1 shows how the PHYSIO DSS is embedded into the overall architecture of the S&R platform. The information flow starts from the field: the values of different health parameters are recorded in the field and transferred directly from the sensors, or entered manually via a front-end application, to the Crisis Management Platform application (CONCORDE) and from CONCORDE to the S&R SOT (strategic, operational, tactical DSS). The SOT DSS communicates with the PHYSIO DSS calling the remote PHYSIO DSS services and returning the updated results related to the victim's physiological status to CONCORDE and from it to the physician in the field. The results are summarized in terms of ETD distributions. Fig. 2 shows a page of the user-interface reporting the results of two subsequent calls to the PHYSIO DSS web-services: on the left panel it is shown the ETD distribution for a victim, computed at 13:22 during the execution of S&R Use Case "Victims trapped under the rubble" hold in Madrid in December 2022; panel on the right shows the updated distribution computed some minutes after, at 13:31, and based on the acquisition of new measurements related to victim health parameters.

Table 1
List of the main elements constituting the PHYSIO DSS tool.

Element	Short name	Description
Physiological State Variable	PSV	10 dimensions used to describe the physiological conditions of the victims (see Table S1).
Values assumed by the PSVs	X	PSV values in the range [0,1]. The value 1 corresponds to perfect conditions along the corresponding dimension, the value 0 corresponds to the complete lack of functionality of the considered dimension.
Rates of change of the PSVs	V	Rates of changes are in the domain of R: they assume negative values if there is a worsening (caused by a lesion) in correspondence of the related PSVs; they assume positive values if there is a restoring (by a means of treatment deliver) of the related PSVs.
Physiological Distributional State	PDS	Probability density of the values X and of the rates of change V of the PSVs. The PDS is a collection of four matrices: two contain the interval extremes of X and V and two contains the relative frequencies. Each matrix has 10 columns (*nvar:* the number of the physiological variables). The number of rows is the number of intervals used to build the frequency histograms: the ranges of X and V have been divided into a number *nbins* of small intervals. The PDSs summarize where the victims are in the PSVs' space from a probabilistic point of view.
Encoded long character string	PIE	A long string related to each victim and containing all their information, both demographic (such as age, weight, height, gender) and related to their physiological state (PDS). In addition, the PIE contains means, standard deviations, medians and modes of the variables X and V; the identification number (ID) of the victim; the time (in posix format) at the which the information refers to.

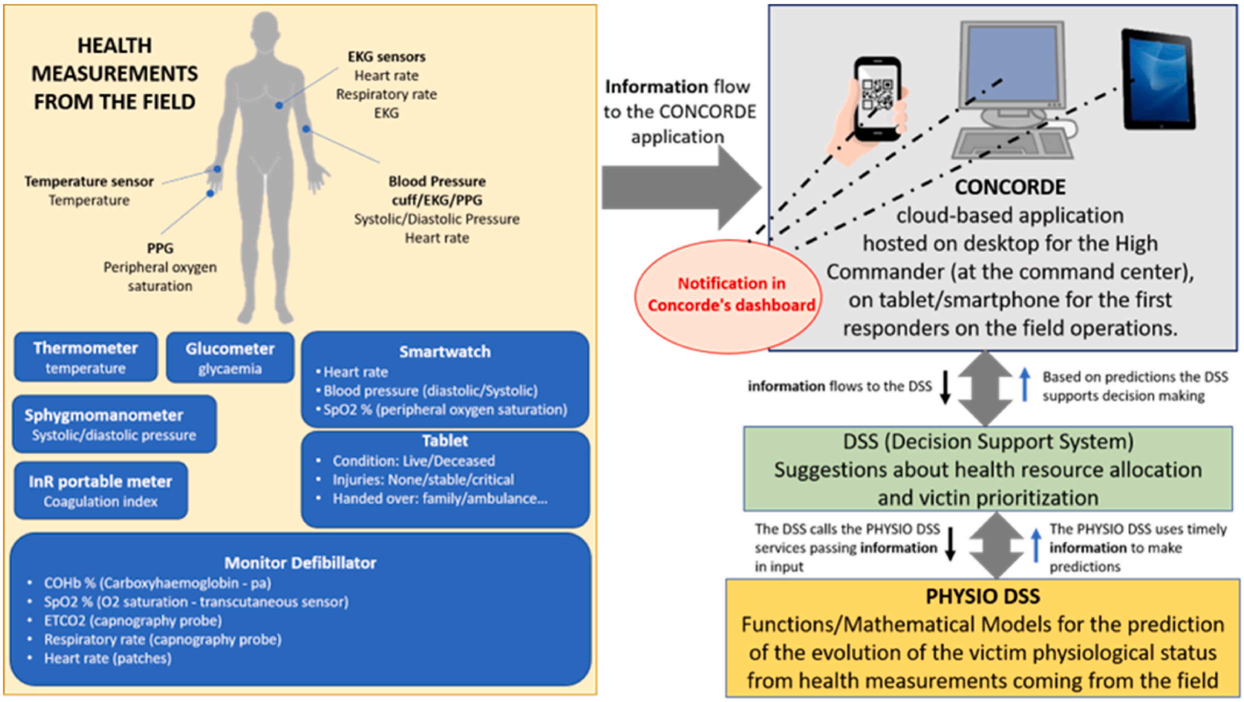

Fig. 1. Information flow from the field to the DSS. Flow of information from the field to the CONCORDE application (Crisis Management Platform) and from CONCORDE to the S&R SOT (Strategic, Operational, Tactical) DSS. The SOT DSS communicates with the PHYSIO DSS calling the remote PHYSIO DSS services. Information comes back to the SOT DSS and to CONCORDE which shows the updated results and provides suggestions to the field.

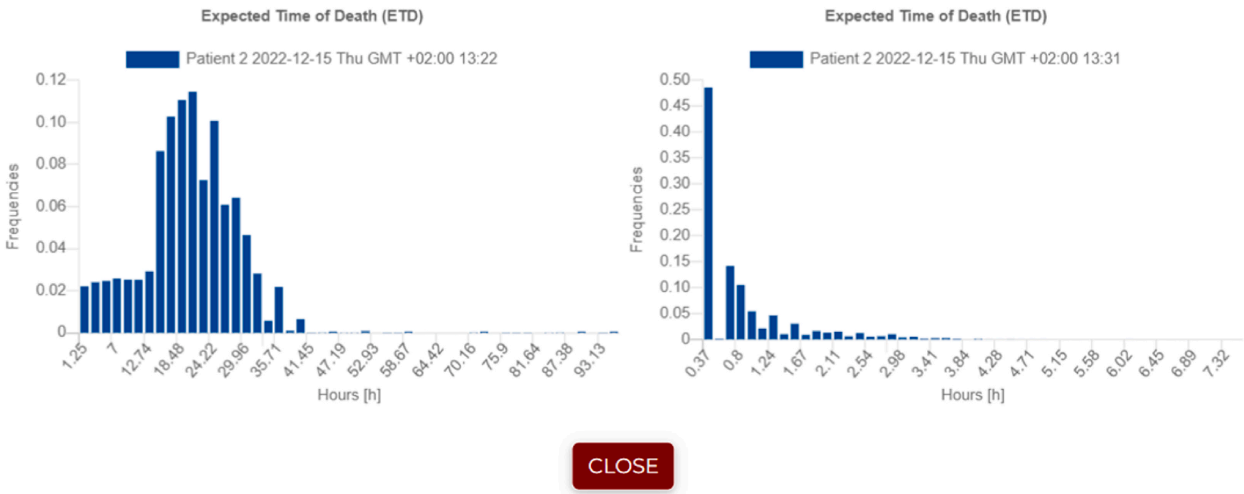

Fig. 2. User-interface for victim's updated information. Panel on left shows the ETD distribution for a victim computed at 13:22 during the execution of the S&R Use Case "Victims trapped under the rubble" hold in Madrid, in December 2022. Panel on the right shows the updated ETD distribution computed at 13:31, exploiting new observations of the same victim taken 9 min after the first available measurements.

As mentioned above the ETD distributions are derived by the distributions of 10 PSVs (each one representing a physiological subsystem and taking values in the interval [0,1], with 1 being the maximum of the physiological functionality) and by the associated distributions of their rates of changes (taking values in R). Table S1 reports a description of the considered 10 PSVs. The health measurements are instead reported in the first column of Table 2. Section 2.2 shows the details of how the PSV a-posteriori distributions are computed; the term "a-posteriori" is used to indicate that the PSV probabilities are conditional probabilities that results from updating the prior probabilities with new information via the application of the Bayes' rule every time a new observation on the victim becomes available; otherwise, the physiological status evolves freely according to the rates of changes of the PSVs.

While the core of the PHYSIO DSS is that of predicting the physiological evolution of a victim, and therefore the evolution of the ETD, other functions and algorithms have been made necessary for testing its functionalities, as for example the generation of an

Table 2
Relationship between Health measurements and the physiological state variables (PSVs).

Health measurement	Interaction with the PSVs	Probability of interaction with the PSVs [%]	Normalization of the Health measurement (Y)
Heart Rate	< Normal – C1, B3 > Normal – C1, B3, C2 Normal – E	C1 (100 %) B3(100 %) C1(100 %), B3 (30 %), C2 (90 %) E1 (50 %)	[0,1]
O2	Normal – A1, C1, C2 Always – B1, B2, B3, D1, D2	A1(100 %), C1(30 %), C2(50 %) B1 (70 %), B2(80 %), B3(80 %) D1 (100 %), D2 (100 %)	[0,1]
Temperature	Normal – E1 > Normal – E1, C1, B3, D1, D2 < Normal - E1,C1,C2	E1(30 %) E1 (50 %), C1(100 %), B3(100 %), D1 (100 %), D2 (100 %) E1 (50 %), C1 (100 %), C2 (100 %)	[0,1]
Skin	Flushed – E1 Not Flushed – C2	E1 (10 %) C2 (100 %)	if normal Y = 0 if pale Y = 0.5 if flushed Y = 0.5
Breathing	Normal – A1, B1, B3 Always – B2, C1	A1(100 %), B1(100 %), B3(50 %) B2 (100 %), C1(100 %)	if normal Y = 0 if Labored Y = 0.5 if Shallow Y = 0.5 if Abnormal Sounds Y = 0.3
Glasgow Coma Scale	Always – D1, D2 GCS < 8 – A1, B1, B3	D1 (100 %), D2 (100 %) A1(100 %), B1(100 %), B3(100 %)	[0,1]
Respiratory Rate	Normal – A1 < Normal – B1, B3 > Normal – B2, B3	A1 (100 %) B1 (100 %), B3(100 %) B2 (80 %), B3 (50 %)	[0,1]
Blood Pressure	Normal – C2 >Normal – D1, C1, B3 < Normal – C2, C1, B3	C2(100 %) D1 (10 %), C1(100 %), B3(100 %) C2 (100 %), C1 (60 %), B3(100 %)	[0,1]
rightPupil and leftPupil	< Normal or > Normal – D1, D2	D1(100 %) D2(100 %)	if out of range Y = 0.7
Airway	Always – A1, B3	A1 (100 %), B3(100 %)	if 0 (false/blocked) Y = 1 if 1 (true/open) Y = 0
Capillary refill	Always – C1	C1 (100 %)	if 0 (abnormal) Y = 1 if 1 (normal) Y = 0

event. Moreover, additional features have been implemented in the PHYSIO DSS tool to automatically and deterministically compute scores of the most used algorithms for triage (START, SIEVE scores, etc …).

A brief description of the taxonomy used by the PHYSIO DSS is reported below. Beyond a series of functions and algorithms, the PHYSIO DSS architecture encompasses a series of *classes*, each one being a collection of *items*.

- *Events* class: a collection of a series of *incidents* (Table S2);
- *Injuries/Lesions* class: a collection of a series of *lesions* that can affect a victim during an event (see Table S3 for a complete list of injuries according to the ICD-9-CM ECOI classification and Table S4 for a simplified description of injuries occurring during an earthquake accompanied by their maximum probability of occurrence and their maximum severity);
- *Treatments/Medications* class: a collection of a series of *therapies/medications* that can be administered to a victim to restore their physiological status (see Table S5);
- *Health measurements* class: a collection of a series of *health measurements* that can be measured and observed on an individual and that are necessary to represent their physiological status (e.g. Glascow Coma Scale, airway patency, capillary refill, etc.) (see column 1 in Table 2).

A schematic representation of the architecture of the PHYSIO DSS is shown in Fig. 3. The figure shows the relationships among the sub-components of the tool both when a crisis is generated (upper side on the left) or when it is a real event (downside on the right). Each incident provokes the occurrence of victims affected by one or more injuries, more or less severe. For each victim, simulated or real, the PHYSIO DSS generates an a-priori distribution of the PSVs and of the rate of change according to the initial injuries (see the next section on the way they are generated) that cause impairments on one or more physiological state variables. Over time the distributions of the PSVs are updated based on both the observations of health parameters and possible administered treatments.

2.2. Lesion generation and computation of the "a-priori" PSV value and rate of change distributions

Once the event occurs the flow of information processing is the same whether it is a simulated or a real. At the beginning of the process, the incident provokes a random number of victims, from a minimum and maximum which depend on the event type, each one affected by a series of *lesions/injuries* with its own severity. For each individual the lesions are randomly extracted with a probability depending on the type of the event. Table S4 reports the lesions considered in an earthquake with the maximum probability of occurrence and the maximum severity. The table has been agreed upon with the experts in the field in the framework of two tabletops organized during the project with the purpose of validating the S&R DSS. Starting from the content of Table S4 for each generated individual the probability of having a lesion ℓ and its severity are inversely related to the distance of the victim from the event lo-

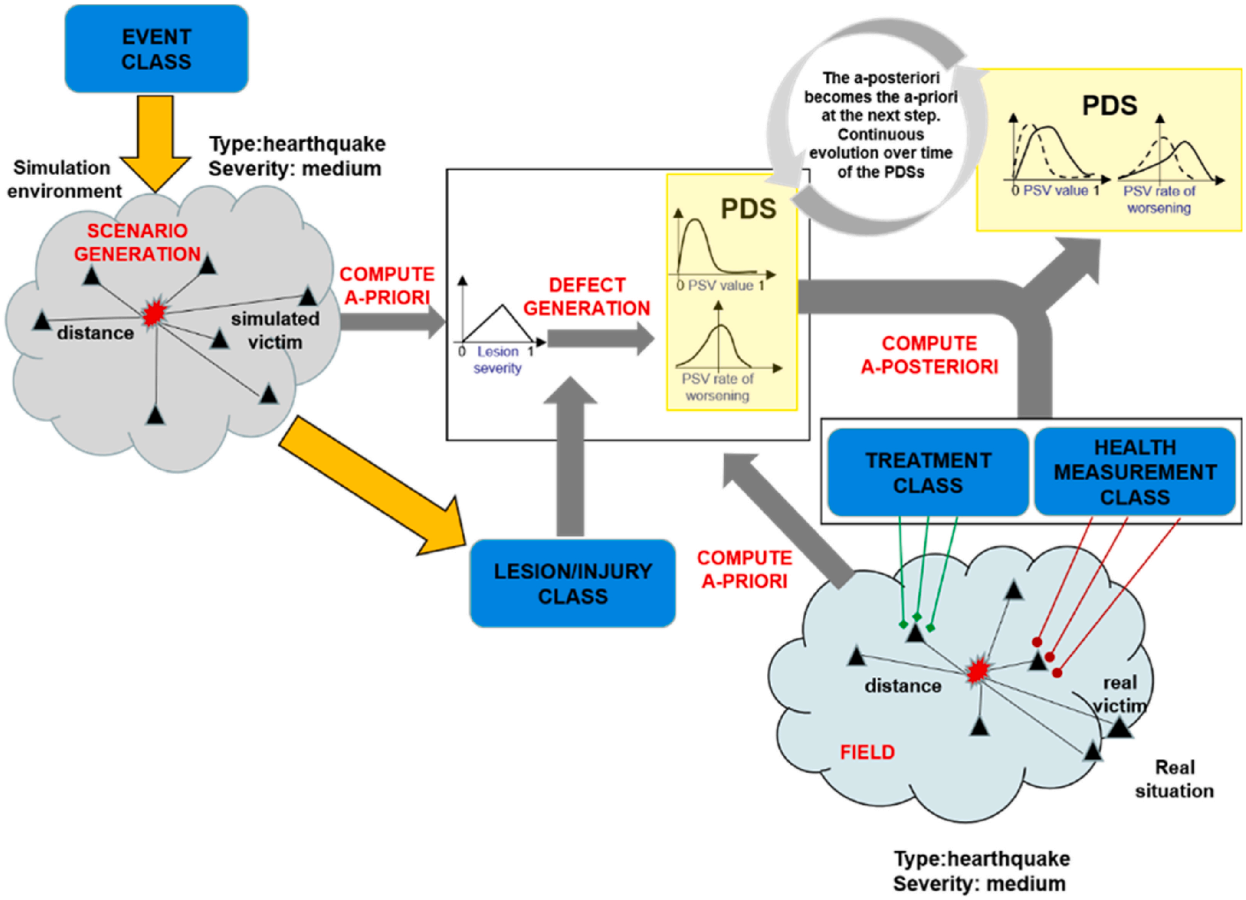

Fig. 3. Architecture of the PHYSIO DSS component. A crisis can be generated (upper side on the left) or can be a real event (downside on the right). Each incident provokes the occurrence of victims affected by one or more injuries, more or less severe. For each victim of the incident (simulated or real) the PHYSIO DSS generates an a-priori distribution of the PSVs and of the rate of change according to the initial injuries that cause impairments on one or more physiological state variables. Over time the distributions of the PSVs are updated based on both the observations of health parameters and possible administered treatments. The update is performed by implementing a fully Bayesian approach (when new observations become available), and/or by the computation of new PSV distributions from a stochastic cause/effect relationship Treatment-PSVs.

cation: individuals at zero distance present the maximum probability of having a lesion (Table S4). The equation below reports the probability of presenting the lesion ℓ for the individual i at normalized (with respect to the event dimension) distance $\overline{distance}_i$ from the event location:

$$l_{pi\ell} = l_{P\ell} \times e^{\left(-\gamma \times \overline{distance}_i\right)} \tag{1}$$

where $l_{P\ell}$ is the maximum probability of occurrence for the given lesion ℓ during the considered event.

The severity of the lesion is drawn from a triangular distribution with modal value inversely dependent on the distance from the event:

$$lesion\_severity_{i\ell} = \begin{cases} 1 - \sqrt{(1-u) \times \left(1 - l_{mi\ell}\right)}, u \geq l_{m\ell} \\ \sqrt{u \times l_{mi\ell}}, otherwise \end{cases} \tag{2}$$

where u is a random number from a uniform distribution and $l_{mi\ell}$ is the individual modal severity computed as:

$$l_{mi\ell} = l_{M\ell} \times e^{\left(-\gamma \times \overline{distance}_i\right)} \tag{3}$$

with γ a constant value. Parameter $l_{M\ell}$ is the maximum modal severity for the lesion ℓ as reported in Table S4. Therefore, each victim presents their own maximum probability of a lesion and its associated maximum modal severity as a decreasing function of the distance of the victim from the site of the incident (i.e. the epicentre of an earthquake).

For each individual i and for each lesion ℓ, we generate a set of 1000 lesion severities ($lesion\_severity_{i\ell j}$ with j referring to the j-*th* realization) so to obtain a distribution of the lesion severity.

Each lesion ℓ causes an impairment on one or more physiological variables: as an example, Table S6 reports the maximum instantaneous impairment (d_M) caused by a chest trauma and by a head trauma on the PSVs, as well as the maximum decrease per hour (a_M) of the PSV functionalities following the two lesions. For each individual i the instantaneous impairment (δ_{ikj}) and the rate of decrement (α_{ikj}) for each k-*th* PSV are drawn from normal distributions with parameters (mean and standard deviation) computed as function of the maximum values reported in Table S6 and of the previously computed lesion severities:

$$\mu_{\delta_{ikj}} = \sum_{\ell} \left(lesion\_severity_{i\ell j} \times \delta_{M\ell k} \right) \tag{4}$$

$$\mu_{\alpha_{ikj}} = \sum_{\ell} \left(lesion\_severity_{i\ell j} \times \alpha_{M\ell k} \right) \tag{5}$$

The two above equations consider for each PSV that the correspondent instantaneous impairment and the rate of change are determined by the additional effects of each lesion ℓ experienced by the subject and determining a damage on the PSV. The individual instantaneous impairment on the PSV k, δ_{ikj}, and the corresponding individual rate of change, α_{ikj}, are derived as it follows:

$$\delta_{ikj} \sim N\left(\mu_{\delta_{ikj}}, \sigma_{\delta_{ikj}}\right), \alpha_{ikj} \sim N\left(\mu_{\alpha_{ikj}}, \sigma_{\alpha_{ikj}}\right), \tag{6}$$

where $\sigma_{\delta_{ikj}}$ and $\sigma_{\alpha_{ikj}}$ are $\mu_{\delta_{ikj}}/8$ and $\mu_{\alpha_{ikj}}/2$, respectively. For each victim the final a-priori distribution of the values and rate of change of each PSV is computed as empirical distribution of the obtained 1000 realizations indexed by j as it follows:

$$X_{\text{a-priori}\,ijk} = 1 + \delta_{ikj} \tag{7}$$

$$V_{\text{a-priori}\,ijk} = \alpha_{ikj} \tag{8}$$

The above procedure generates the a-priori distribution of the values and of the rates of change of the PSVs on the basis of very little information immediately available from the field, such as the type of incident and the location of the victim with respect to the incident site (how far away the individual is). Of course, it is assumed that any anatomical lesion verifies, a-priori, with an expected probability (third column in Table S4) which resembles the frequency with which it occurs in that type of event considered. This information can be retrieved from the analysis of databases related to past crisis events or by a confrontation with experts in the field.

2.3. Computation of the "a-posteriori" PSV value and rate of change distributions given the health measurement

The evolution of the victim's physiological status depends on both the administered treatments and on the retrieved information from the field (see the *Health measurements* instances in the first column of Table 2). The update is performed by implementing a fully Bayesian approach (see equation (9) below) when the new information is related to the observation of health parameters, or by the computation of new PSV distributions from a stochastic cause/effect relationship between PSV and Treatments when a treatment is administered. Although, the treatment delivered does not enter the distributional updating process by means of a Bayesian approach, the updated distribution is still referred to as a-posteriori distribution (as it derives from the combination of "new" and "old" knowledge). Table 3 lists the external functions accessible from a client calling the PHYSIO DSS services. The "*ComputeAposterioriGivenHealthMeas*" function updates the current state based on health parameter observations. The process is continuous and at a specific temporal point the computed a-posteriori distributions become the a-priori distributions at a subsequent time instant.

The functioning underlying the "*ComputeAposterioriGivenHealthMeas*" code is based on a series of relationships/dependencies between the health measurements and the physiological variables. The dependence exists when the observed health parameter gives information on the possible values that one or more PSVs can assume (that is information on some physiological aspects). For example, when normal, the blood pressure gives information on the "Decreased central venous pressure and cardiac filling and increased systemic vascular resistance" variable (C2) with a 100 % of probability (a normal blood pressure implies no impairment of C2). Conversely, when the blood pressure is high (above the superior extreme of the normality range), the measurement always provides infor-

Table 3
External PHYSIO DSS Webservices functions accessible from the client.

Function name	Output
ComputeAprioriGimelTuple	A-priori empirical distribution of the PSVs from very few initial information on the victim
ETDPIEVector	Empirical distribution of the expected time to death
ComputeAposterioriGivenHealthMeas	A-posteriori empirical distributions of the PSVs given the observed value of health parameters
ComputeAposterioriGivenTreatment	A-posteriori empirical distributions of the PSVs given the values of the delivered treatments
PhysioEVO	Update of the current PIE on the basis of a free evolution of the system
GlascowComaScaleComputation	Glascow Coma Scale (score between 3 and 15)
JumpStartTriage	Triage code according to the Jump Start algorithm
SieveTriage	Triage code according to the Sieve algorithm
SortTriage	Triage code according to the Sort algorithm
StartTriage	Triage code according to the Start algorithm

mation on the variables “Oxygen transport” (B3) and “Heart pump function” (C1) (with a 100 % of probability) and in 10 % of cases on the variable “Central nervous System function” (D1). When the blood pressure is below the lower limit, the measurement gives insight into the C2, C1 and B3 PSVs with 100 %, 60 % and 100 % probability, respectively. Table 2 shows the set of relationships implemented. According to the Bayes’ Theorem [28], the a-posteriori distribution of a generic Physiological Variable $p_{X|Y}(x)$ is given by:

$$p_{X|Y}(x) = \frac{p_{Y|X}(y)p_X(x)}{\int p_{Y|X}(y)p_X(x)\,dx} \tag{9}$$

where X represents the PSV (e.g. the “Oxygen transport”, PSV4) and Y is the normalized health measurement observation (e.g. the heart rate measurement reformulated between 0 and 1). The function $p_X(x)$ represents the a-priori distribution of the physiological variable X, as output of the “*ComputeAprioriGimelTuple*” function, or as the a-posteriori distribution computed at a previous time (as a result of the “*ComputeAposterioriGivenHealthMeas*” function). The conditional probability distribution $p_{Y|X}(y)$, is instead, computed as showed in the next subsections. In the same way the a-posteriori distributions of the rates of change are derived. The following subsections describe the reasonings underlying the computation of the $p_{Y|X}(y)$ starting from the health measurement normalization process.

2.4. Health measurement normalization

The domain of each observed quantitative health parameter was set to [0,1] by a transformation which normalizes the original measurements. Values of the original measurements that lay within the normality range determine normalized values close to 0 while values that are far from the normal range bounds produce values closer to 1:

$$y = \begin{cases} 0 \; x \in [l,u] \\ e^{-\lambda_m(x-m)} \; x < l, x \geq m \\ e^{-\lambda_M(M-x)} \; x > u, x \leq M \\ 1 \; otherwise \end{cases} \tag{10}$$

where.

- y is the normalized health measurement;
- x is the original observed health measurement;
- u is the upper normal range of the health parameter;
- l is the lower normal range of the health parameter;
- λ_m is the rate of decrease of the normalized value from 1 to 0 as the measurement approaches the lower extreme of the normality range;
- λ_M is the rate of decrease of the normalized value from 1 to 0 as the measurement approaches the upper extreme of the normality range;
- m is the minimum acceptable value of the observed health parameter;
- M is the maximum acceptable value of the observed health parameter.

Fig. 4, Panel A, shows graphically the normalization process applied to the heart rate and the systolic blood pressure.

For health parameters, such as “Skin”, “Breathing”, “Airway” and “Capillary refill” which assumes categorical values, as well as for the right and left pupil assessment, the normalized values Y are reported in the last column of Table 2.

2.5. Computation of the conditional distribution $p_{Y|X}(y)$

For the conditional probability function $p_{Y|X}(y)$ in equation (9) we adopted a triangular distribution on the interval [0,1] with parameters a, b and c depending on the values of the variable X (one of the PSVs), where a is the inferior extreme of the support of (Y|X), b is the superior extreme of the support and c is the mode of the distribution. As shown below, the shape of $p_{Y|X}(y)$ changes according to the values of X. Values of X close to 1 (that is no impairment of the physiological variable) give rise to conditional distributions presenting high probabilities in correspondence of zero; this translates into high likelihood of health measurement values within the normality range. Contrarywise, low values of X (that is presence of defect on the physiological variable) produce a distribution for (Y|X) with high probabilities in correspondence of 1 (that means high likelihood of health measurement values outside the normality range), see Fig. 4, Panel B. The adopted parametrization makes the support of Y|X smaller and concentrated towards the value 0, so that very small values are more likely, when X assumes large values, larger than the pre-specified superior thresholds of 80 %; the support of X|Y becomes smaller and concentrated towards the value 1 (therefore with values near 1 more likely) when the values of the physiological variable are smaller than the inferior pre-specified thresholds of 20 %. The equations below report the parametrization adopted for $p_{Y|X}(y)$:

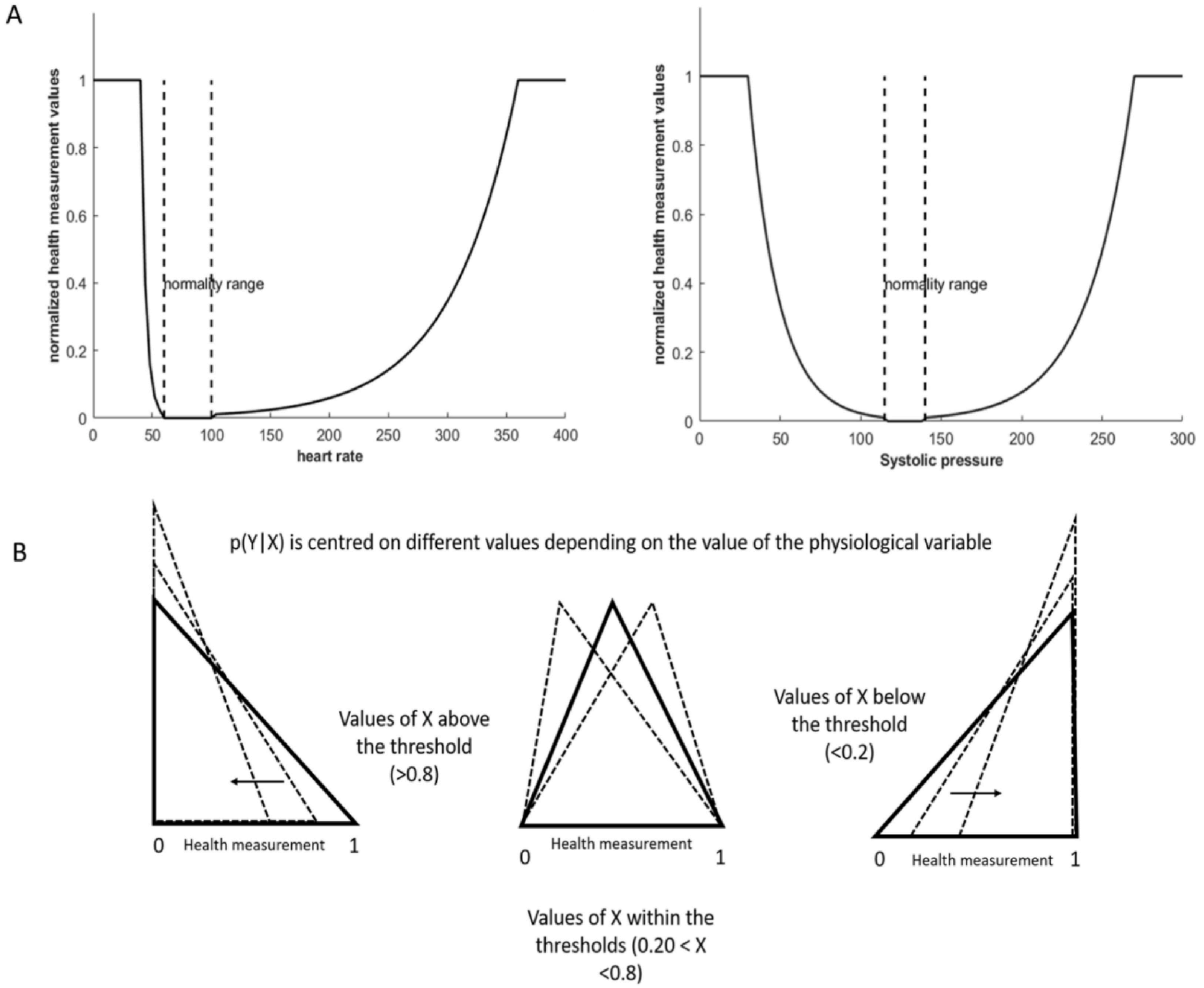

Fig. 4. (Panel A) Normalization of the Health measurements. Example of the heart rate and systolic pressure normalization. When the observed original parameter is within the normality range the normalized value is close to zero; on the contrary when the original observation is far away from the limits of the normal range the normalized value approaches one. (Panel B) Conditional probability distribution p(Y|X). The probability distribution of the health measurement given the value of the PSV, p(Y|X), follows a triangular distribution in the interval [0,1], parametrized by the value of X. High values of X (no or very small impairments on the considered PSV) determine a distribution p(Y|X) with high probabilities in correspondence of zero. Contrarywise, low values of X (that means presence of defect on the considered PSV) determine a distribution p(Y|X) with high probabilities in correspondence of 1. The support of Y|X becomes smaller and concentrated towards the value 0, making very small values more likely, when X assumes values larger than the pre-specified superior thresholds of 80 %; the support of X|Y becomes smaller and concentrated towards the value 1 when the values of the physiological variable are smaller than the inferior pre-specified thresholds of 20 %.

$$p\left(y|x_t\right) = \begin{cases} \dfrac{2}{b-a}\dfrac{y-a}{c-a}, if\ a \le y < c \\ \dfrac{2}{b-a}, if\ y = c \\ \dfrac{2}{b-a}\dfrac{b-y}{b-c}, if\ c < y \le b \end{cases} \tag{11}$$

with

$$\begin{cases} a = \dfrac{x_l - x_t}{x_l - c_f} \\ b = 1 \\ c = 1 \end{cases}, if\ x_t \le x_l\ ;\ \begin{cases} a = 0 \\ b = 1 - \dfrac{x_t - x_l}{1 - x_u} + c_f, if\ x_t \ge x_u; \\ c = a \end{cases} \begin{cases} a = 0 \\ b = 1 \\ c = 1 - \dfrac{x_t - x_l}{x_u - x_l} \end{cases}, otherwise \tag{12}$$

Parameter $c_f = 0.01$ is a correction factor; x_l and x_u are the inferior and superior thresholds of the PSVs.

2.6. Computation of the “a-posteriori” PSV value and rate of change distributions given the treatment administration

The PIE (the object that contains all the related victim information) at a certain time can also be updated on the basis of the treatments/manoeuvres/medications delivered to restore the values of the physiological variables after injuries have caused impairments. Also, in this case the focus is in the computation of the probability distributions of the PSVs given the treatment, that is with the treatment T being the conditioning variable. The treatment value is transformed into its normalized value $\overline{T}$, which assumes values between 0 and 1 and represents the proportion of the maximum quantity that can be administered for that treatment. In case of a treatment that can be delivered or not delivered, as for example in case of a “wound cleaning”, it will be a binary variable assuming values 0/1. The administration of a treatment will always have a positive effect on the values and/or rates of change of the physiological variables. The computation of the a-posteriori distributions $p_{X|T}(x)$ and of $p_{V|T}(x)$ is also a stochastic process as the effect of the treatment (both in terms of variation of the values of the physiological variable and of its rates of change) is not deterministic but it is drawn from a normal probability distribution centred on an expected effect ($\mu^T_{\delta_{ik}}$ and $\mu^T_{\alpha_{ik}}$) depending from the normalized value of the delivered treatment and from the maximum effect that the treatment can exert on the PSV's values and rates (δ^T_{Mrk} and α^T_{Mrk}, respectively, with r that represents the r-*th* treatment and k that represents the k-*th* PSV). Below the formalization adopted:

$$\mu^T_{\delta_{ik,r}} = \overline{T}_{ir} \times \delta^T_{Mrk} \tag{13}$$

$$\mu^T_{\alpha_{ik,r}} = \overline{T}_{ir} \times \alpha^T_{Mrk}. \tag{14}$$

The instantaneous increment $\delta^T_{ik,r}$ and the rate of improvement $\alpha^T_{ik,r}$ for the k-*th* PSV and i-*th* individual in correspondence of the r-th treatment are derived from the following:

$$\delta^T_{ik,r} \sim N\left(\mu^T_{\delta_{ik,r}}, \sigma^T_{\delta_{ik,r}}\right), \alpha^T_{ik,r} \sim N\left(\mu^T_{\alpha_{ik}}, \sigma^T_{\alpha_{ik}}\right), \tag{15}$$

where $\sigma^T_{\delta_{ik,r}}$ and $\sigma^T_{\alpha_{ik,r}}$ are $\mu^T_{\delta_{ik,r}}/8$ and $\mu^T_{\alpha_{ik,r}}/8$, respectively. As an example, Table S7 reports the maximum instantaneous increment (δ^T_M) of each PSV determined by oxygen and blood bags administration, as well as the maximum rate of improvement per hour (α^T_M) in relation to the two treatments. For each victim the final a-posteriori distribution of the values and rate of change of each PSV is computed as the empirical distribution of 10000 realizations:

$$X_{\text{a-posteriori|r } ijk} = \min\left(X^s_{a-priori_{ijk}} + \delta^T_{ik,r}, 1\right) \tag{16}$$

$$V_{\text{a-posteriori|r } ijk} = V^s_{a-priori_{ijk}} + \alpha^T_{ik,r} \tag{17}$$

with $X^s_{a-priori_{ijk}}$ and $V^s_{a-priorii_{ijk}}$ samples drawn from the individual a-priori empirical distributions $X_{a-priori_{ik}}$ and $V_{a-priori_{ik}}$, respectively, for each considered PSV.

2.7. Computation of the expected time to death (ETD) for victim's prioritization

Finally, the Expected Time to Death (*ETD*) function (“*ETDPIEVector*” in Table 3) generates the distribution of the expected physiological time of death (ceasing of the victim's vital functions) based on the distributions of the values and rates of worsening of the physiological variables. The ETD is the minimum time necessary for the subject to reach a value incompatible with life (zero value), among the physiological variables and can support the decision maker in victim prioritization. The ETD function can also be used to establish the best treatment to administer to a victim by comparing the ETD distributions (or their averages) for different potential treatments. Given the distributions of the values and rates of change of the PSVs at a time t ($X(t)$ and $V(t)$, respectively) the distribution of the ETD for the victim i is computed as the empirical distribution from 10000 realizations as it follows:

$$ETD_{ij}(t) = \min\left(96, \min_k\left(-\frac{X^s_{ikj}(t)}{V^s_{ikj}(t)}\right)\right) \tag{18}$$

where $X^s_{ikj}(t)$ and $V^s_{ikj}(t)$ are the j-th realizations from the distributions $X_{ik}(t)$ and $V_{ik}(t)$, respectively. From the previous equation it follows that the ETD is superiorly limited at 96 h (that is 4 days), since a patient with an expected time to death equal or larger than 4 days, for the purpose of the present methodology, is considered out of danger.

2.8. Implementation of the PHYSIO DSS

The PHYSIO DSS for the S&R project was built as a web service running on a LAMP server located at the CNR-IASI BioMatLab. The functionalities offered are described by the Web Services Description Language (WSDL) at [29] and make use of the Simple Object Access Protocol SOAP messaging protocol. The web service natively supports interoperable machine-to-machine (M2M) interaction over a network, as its interface is described in a machine-processable format. The proposed architecture does not impose any further interoperability constraints. Any language can be used to program a client, as long as it follows the public interface of the web service and respects the SOAP [30] specifications. The requests and responses are exchanged in Extensible Markup Language (XML) language [31].

3. Results

The next subsections present the results of several simulations, providing insights into how the PHYSIO DSS can support crisis management from the health care system and health monitoring point of view.

3.1. Simulation of an earthquake

We start by simulating a crisis event for victim generations with the final aim of showing the PHYSIO DSS capability in predicting the victims' physiological status evolution. An earthquake of medium severity has been generated. Table S2 reports, in correspondence of ID = 2, the parameters adopted for the specific scenario (earthquake). Additional inputs were the dimension of the event (set to 100 m), to represent the extent of the involved area and the severity of the event (set to MEDIUM = 0.5). Table S4 reports the subset of the considered injuries, along with their respective maximum probability of occurrence and maximum severity. The simulation generated 491 victims, each one with the associated latitude and longitude deviations (expressed in meters) from the incident location and sampled from a triangular distribution (with mode the epicentre of the earthquake and with the limits of the support the event dimension in positive and negative directions). The location of the 491 victims is shown in Fig. 5, panel A. Panel B shows the histogram of frequencies of the victims' distances from the epicentre.

Fig. S1 reports the histograms of frequencies of the severities of three injuries for a victim who lies very close (red bars) to the epicentre and for a victim at a large distance from the event location (green bars). While during an earthquake the injuries head and chest trauma are very common to occur, hypothermia, is supposed to be less frequent and less severe. The empirical distributions of the average severities of the head trauma injury for all the victims that lie less than 30 m (red bars) or more than 50 m from the epicentre (green bars) are reported in Fig. S2.

3.2. Simulation of the evolution of the victims' physiological status

Each injury provokes an impairment in some or all the physiological variables. The defect is expressed in terms of instantaneous decrement of the PSV (for a healthy individual the distributions of the PSVs are concentrated on the value 1) and in terms of worsening (decrement) of rates of change (which cause a shift of the PSVs' distributions from 1 towards non-physiological values until they reach the zero value). Table S6 shows an example of how the injuries affects the PSVs. Inputs from the table are used to generate the a-priori distributions. Three movies provided in the multimedia appendix demonstrate the potential of the PHYSIO DSS in terms of the information it provides on a victim when integrated into a user application (such as an app for tablet or smartphone): the medical commander in the field is able to follow the evolution over time of the patient's health status by monitoring the change of the physiological variable and ETD distributions (panels on the right), updated every time a new observation (heart rate, respiratory rate, etc …) is made available (panels on the left show how the values of the health parameters vary over time).

Movie 1 shows the evolution over time of the ten PSV distributions, along with the distribution of the expected time to death, for a victim located at 80 m of longitude and latitude, and who presents the values of the health parameters reported in Table S8. In the movie, as time passes, the health measurements are taken in the order reported in the last column of the table. All the measurements are in the normal range, highlighting that the victim, with high probability, is not affected by any important injury. At the beginning of the movie the blue bars represent the a-priori distributions of the PSVs, computed only based on the information related to the victim's position with respect to the event location. The green bars are the updated distributions computed after each new health para-

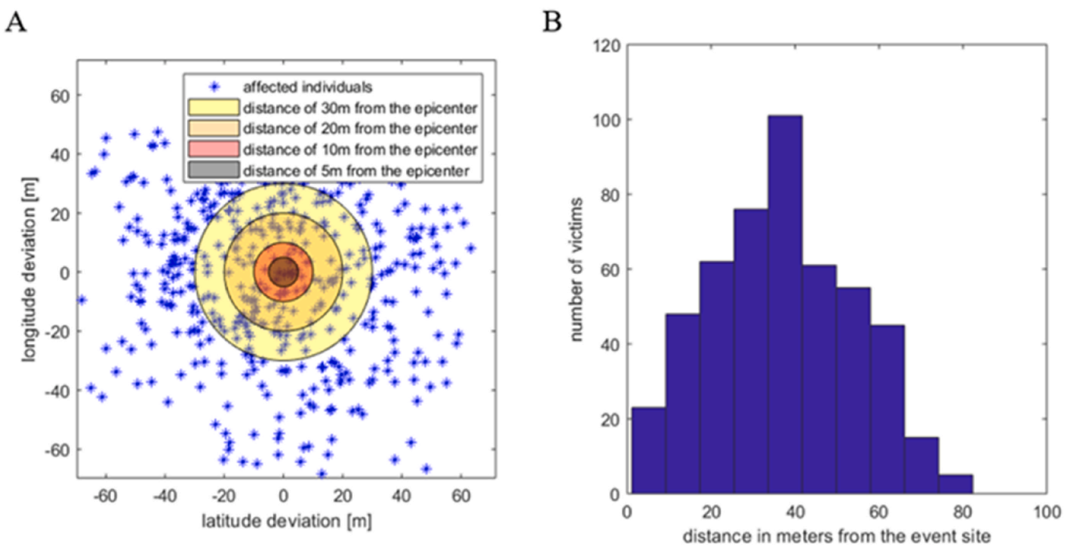

Fig. 5. Scenario generation and victim locations. (Panel A) Location of the simulated victims at different distances in terms of longitudinal and latitudinal deviations [m] from the epicentre of the earthquake. (Panel B) Empirical distribution of victim distances from the earthquake epicentre. Absolute number of victims in correspondence of different distances from the epicentre of the event.

meter observation is made (panels on the left). All the health measurement values have been normalized in the range [0,1] as described above. The bottom panel on the right shows the ETD distribution, with the vertical line representing the average of the distribution. Movie 2 shows the evolution of a victim located at a small distance from the event location (10 m for both the longitude and latitude) whose health measurements are reported in Table S9 (red values are out of the respective normality ranges). It is already evident from the shape and position of the a-priori distributions, that the system foresees for this victim, with substantial probability, several lesions with a certain degree of severity. With respect to the previous simulation, some of the a-priori PSV distributions (blue bars) span over a range including values also below 0.5. The simulation has been built to represent a victim affected by head trauma and whose measurements, taken over time in the order as they appear in the associated table, shift the ETD distribution towards smaller values, lowering the average ETD to about 10 h. Movie 3 shows an individual that at the start of the simulation presents normal conditions (all the measurements are within the normality range, see the second column of Table S10). Over time however, some measurements tend to assume abnormal values (third column of Table S10) simulating the occurrence of an injury, as for example an internal blood loss. The "Heart rate", "Oxygenation", "Respiratory Rate" and the "Blood Pressure" get worse and affect the "Oxygen transport" (PSV4), the "Heart pump function" (PSV5) and the "Central pressure, Cardiac filling and Systemic vascular resistance" physiological variable (PSV6) producing distributions spanning over lower values and a final average expected time to death of about 2 h. The obtained results are strictly dependent on the input relationships between each pair Health measurement-PSV (Table 2).

Supplementary data related to this article can be found online at https://doi.org/10.1016/j.ijdrr.2024.104890

3.3. Impact of treatment administration on the PSVs' distributions

In this subsection, we illustrate the impact of treatment administration on PSV distribution patterns. Let us suppose to have a victim with an impairment on the physiological variable "Airway patency". In this situation an immediate treatment is the delivery of oxygen. Fig. S3 shows the effect of the treatment on the probability distribution of both the values and the rates of change of the considered PSV. In presence of an anatomical lesion the delivery of oxygen affects the rate of change of the PSV by reducing it, without affecting its levels as the merely oxygenation does not definitely restore the PSV functionality if the lesion is not healed. This is evident from the superimposition of the a-priori and of the a-posteriori distribution of the PSV values in Fig. S3, panel A. Contrarily, panel B shows an improvement in the rate of change whose distribution moves towards larger value. The magnitude of the effect of a treatment on any physiological variable depends on the strength of the relationship Treatment/PSV which in the current version of the PHYSIO DSS is set to be linear, expressed by coefficients, extracting from a normal distribution, acting on the level of the variable (by increasing it, equation (16)) or on the rates of change (by decreasing their absolute value, equation (17)).

3.4. ETD estimation: possible influence on victim prioritization

To demonstrate the final aim of the PHYSIO DSS with particular reference to the ETD computation, in the following we describe the obtained output, in terms of ETD distributions, for three victims on which "Heart Rate", "Respiratory rate", "Oxygenation" and GCS are observed at subsequent times.

- VICTIM 1: Heart Rate = 60 beats/minute; Respiratory rate = 12 breaths/minute; O2 Oxygenation = 97 %; GCS = 12
- VICTIM 2: Heart Rate = 145 beats/minute; Respiratory rate = 27 breaths/minute; O2 Oxygenation = 99 %; GCS = 15
- VICTIM 3: Heart Rate = 98 beats/minute; Respiratory rate = 32 breaths/minute; O2 Oxygenation = 60 %; GCS = 15

From the reported observations of the four health parameters, it is evident that the physiological conditions of the VICTIM 1 are the less severe with VICTIM 3 who presents the worst conditions requiring a prompt assistance. Fig. 6 shows very similar a-priori ETD distributions (blue bars) with ETD mean values around 6 h.

Apart from a slightly low GCS, the respiratory frequencies and the heart rate for VICTIM 1 are within their relative normality ranges, even if both the observations are near to one of the two extremes, while the oxygenation is fully within the range. After observations are made, the ETD a-posteriori distribution presents a mean value of about 72 h. As for VICTIM 2, both respiratory frequency and heart rate are out of range, resulting in an a-posteriori average ETD of approximately 10 h. For the VICTIM 3, instead, the heart rate is close to the upper limit of the normality range, the respiratory frequency is high while the O2 oxygenation is very low determining a final ETD mean value of about 6.5 h.

3.5. Sensitivity analysis

To address part of the need for a comprehensive sensitivity analysis, this subsection explores the impact of the normalization procedure applied to health parameters in describing victim condition severity. While the entire set of parameter values were carefully validated by domain experts, the normalization method was primarily adopted for programming efficiency. Therefore, its influence on outcomes is worth exploring. Fig. 7 displays normalization curves for different values of parameters λ_m and λ_M in equation (10). The black line represents the reference values for the two parameters used in the preceding simulations. The blue and red lines illustrate the curves for parameter values increased and decreased by 40 % from the reference, respectively. As an example, the sensitivity analysis was conducted for the "Diastolic pressure" and "Heart rate" health measurements. Panel A shows the normalization curves for the "Diastolic pressure", panel B reports the curves for the "Heart Rate". The values of the two parameters determine the curve's shape, influencing the steepness of the trend from zero severity (physiological conditions) to approximately one (increasingly severe conditions).

To isolate the influence of the two parameter values, the following simulations were conducted using a fixed random seed. We simulated a victim with a diastolic pressure of 40 mmHg measured 5 min after the incident. This value is below the lower limit of the

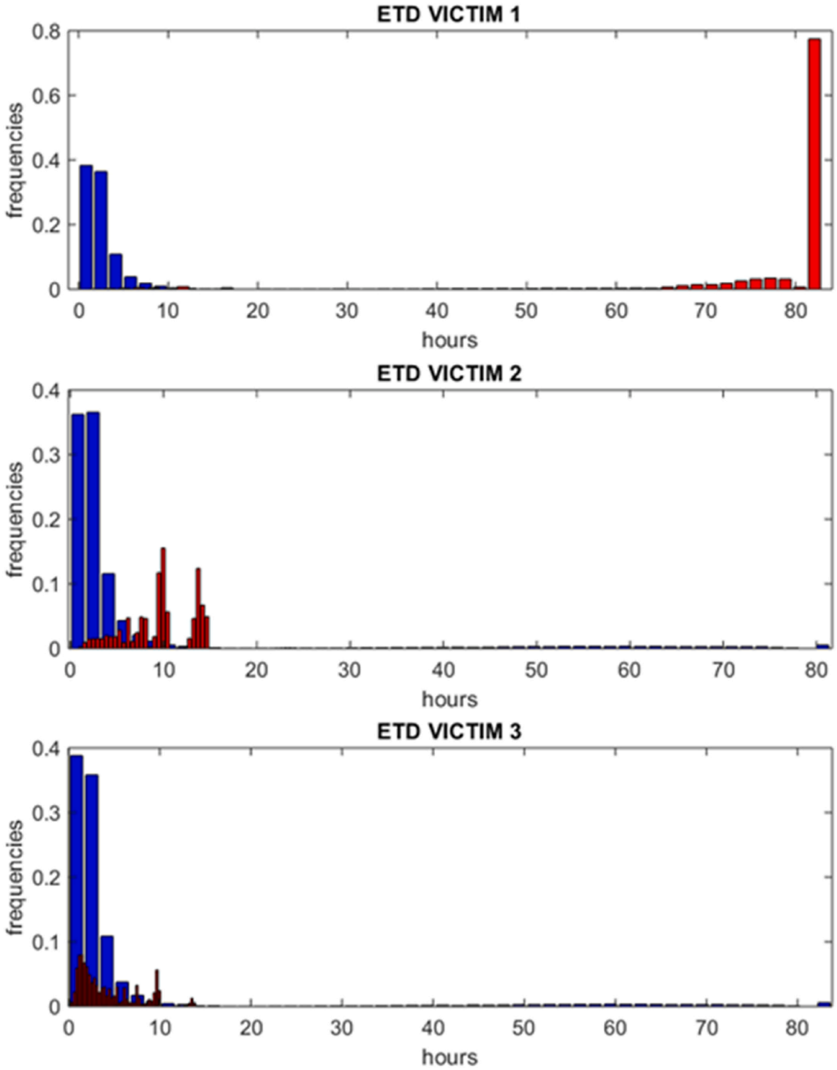

Fig. 6. ETD distributions. Distribution of the Expected Time to death for three victims with progressive degree of condition severity. Blue bars refer to the a-priori distributions; red bars are for the a-posteriori distributions.

normality range. The pressure was then normalized according to the three different curves. For the same victim, we subsequently hypothesized a pressure of 110 mmHg, which exceeds the upper limit of the normality range.

Column 4 of Table 4 reports the a-posteriori average ETD values obtained from the simulations. Conversely, the lower portion of the table presents results for heart rate measurements, both below and above the normal range.

The obtained average ETD values align with expectations and demonstrate that even significant changes (40 %) to certain key parameters minimally impact the results, indicating that the adopted approach is quite robust.

4. Discussion

The PHYSIO DSS was developed as part of the Decision Support System (DSS) of the Search and Rescue H2020 project. The philosophy driving the development of the PHYSIO DSS was that of offering the decision maker not just an overview of what is currently happening during a crisis event or of the current status of the victims, but a (probabilistic) forecast of what will be the status 30 min or 1 h or 6 h in the future. The aim of the present work is that of presenting what is the main core of the PHYSIO DSS component, that is its ability to predict the physiological status of the victims in terms of probability distributions, by updating them on the basis of both observations of health parameters, measurable in the field, and delivered treatments, by implementing a Bayesian approach. From the computation of the distributional form of the PSVs, the PHYSIO DSS is able to derive the distributions of the Expected Time to Death (ETD), which provides additional elements for a more informed prioritization of the victims and resource allocation. It must be underlined that the computation of the ETD is not intended to replace the standard triage algorithms used in practice, but it can be used when different victims have been assessed, according to standard triage algorithms, with the same prioritization score, but with some individuals being in more severe conditions.

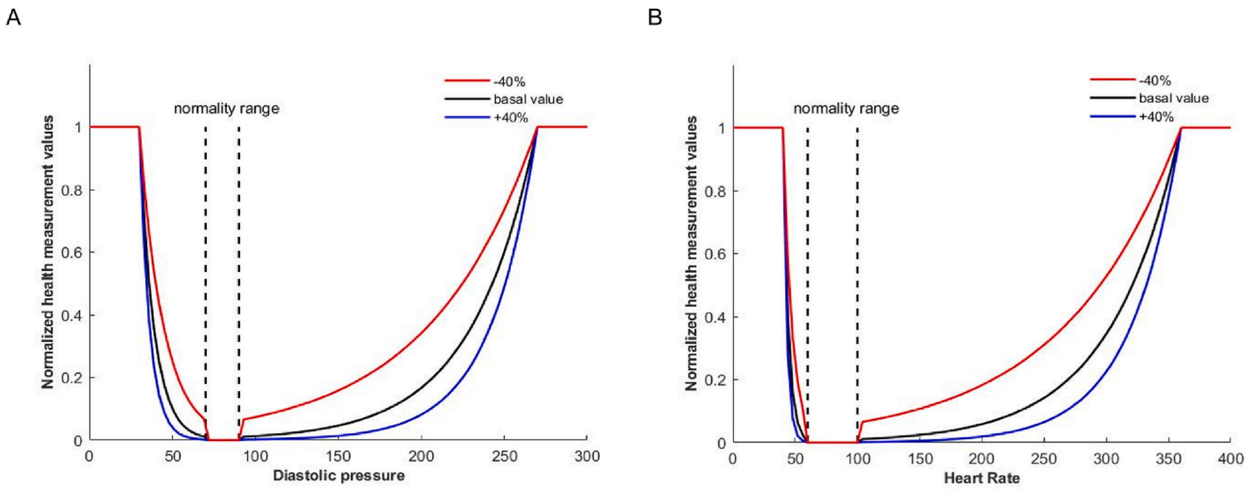

Fig. 7. Normalization curves. Normalization curves for the "Diastolic pressure" (panel A) and for the "Heart Rate" (panel B) obtained by varying parameters λ_m and λ_M. Black lines are in correspondence of the reference values, blue and red lines are obtained by increasing and decreasing by 40 % the reference values, respectively.

Table 4
Sensitivity analysis in correspondence of different health parameter normalization curves.

Diastolic pressure	λ_m	λ_M	Average ETD
40 mmHg	reference value	reference value	15.56
40 mmHg	+40 % of reference value	reference value	17.10
40 mmHg	−40 % of reference value	reference value	12.78
110 mmHg	reference value	reference value	19.72
110 mmHg	reference value	+40 % of reference value	22.39
110 mmHg	reference value	−40 % of reference value	18.16
Heart rate	λ_m	λ_M	**Average ETD**
45 bpm	reference value	reference value	15.32
45 bpm	+40 % of reference value	reference value	16.88
45 bpm	−40 % of reference value	reference value	12.67
250 bpm	reference value	reference value	17.90
250 bpm	reference value	+40 % of reference value	18.78
250 bpm	reference value	−40 % of reference value	15.63

The PHYSIO DSS component is based on a series of functions, algorithms, and hypothesized parameter values, on which an agreement was reached during ad-hoc meetings (two table-top simulations organized as part of the validation process of the S&R DSS) with a commission of experts, made up of three medical doctors chosen based on their expertise in the field of rescue and incident management. The role of the panel was that of providing meaningful inputs and suggestions, particularly on the parameter values, as well as to evaluate and improve the services offered by the S&R DSS. We note however that the focus of the present work was that of presenting the architecture of the PHYSIO DSS and its capabilities, rather than the specific physiologic assessments considered. Results may be further validated by other experts in the field and parameters may be tuned on the basis of a thorough analysis of past events. However, changes in the input parameter values would not modify the structure of the DSS: a supervised calibration of the working parameters could lead to more reliable physiological results. We also remark that the development and implementation of the PHYSIO DSS stems from the improvement of work carried out during two previous European funded projects. The main change with respect to the previous approach is the introduction of stochasticity (uncertainty) in the prediction of the victim physiological evolution. As more thoroughly detailed above, this is based on real-time updates of the available information, combining pre-existing knowledge and new data coming asynchronously from the field, making use of a completely Bayesian approach which computes the a-posteriori distribution from the a-priori distributions and the likelihood of the observations. This change of paradigm necessitated the introduction of a set of relationships, some of them of a probabilistic nature, between the health parameters and the physiological state variables, which were the results of in-depth discussions with the members of the panel of experts.

The decision to provide the PHYSIO DSS as a web service offers several advantages in terms of development and integration. One of the strong points of the PHYSIO DSS is its adaptability in the framework of any DSS thought also for the management of the patient. It was indeed released as a set of Web Services on a client-server, available in a machine-to-machine (M2M) form, requiring no other constraints. Despite the fact that any programming language can be used to set up a client, the server must be interrogated following the instructions exposed in the Web Services Description Language (WSDL), respecting the Simple Object Access Protocol (SOAP) based on the Extensible Markup Language (XML). By relying on standardized protocols, web services ensure compatibility across various systems, facilitating communication and data exchange between different platforms, operating systems, and programming languages. Users are completely unaware of any possible update to the Web Services, as long as there are no modifications in terms of inputs and outputs. Moreover, its high reusability allows integration into multiple applications while sharing a common web service infrastructure. These factors make the PHYSIO DSS a valuable resource for developers of DSS in the crisis management domain and makes it suitable to be embedded into any App or personalized health care systems and wearable devices for remote health monitoring.

A primary limitation of the PHYSIO DSS resides in the difficulty of establishing a robust validation process in real-world scenarios, compounded by the inherent subjectivity in parameter value selection. Despite in-depth discussions during the two dedicated tabletops, elements of arbitrariness persist in the choice of parameters.

Further refinements of the underlying mathematical modelling and parameter values are possible through further discussions with experts in the field, such as physicians and crisis managers. However, the proposed tool was tested during a real Use Case (Use Case 7, "Victims trapped under the rubbles") planned in the framework of the Search & Rescue project; the obtained results were completely in line with what was expected, and the tool was judged by the Commander-in-the-field professionals participating in the Use Case, as a real help in prioritizing victims and organizing a confused field situation. Undoubtedly, a comprehensive sensitivity analysis evaluating the influence of individual and combined parameter values would provide deeper insights into the system's validity. Although in this study we only addressed the impact of the normalization procedure on the average ETD value, the observed limited output variations despite substantial changes to two key parameters hint at system robustness. Nevertheless, a thorough sensitivity analysis, demanding significant computational resources, merits dedicated future research.

In conclusion the PHYSIO DSS, with its intrinsic adaptability, interoperability and scalability, which makes it easy to be integrated into various existing applications, is able to provide more accurate and timely information on the physiological status of a victim. This more accurate assessment of the victim's severity conditions allows for improved patient care, aiding in better decision-making for rescue and incident management in crises.

CRediT authorship contribution statement

Simona Panunzi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Marcello Pompa:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software. **Alessandro Borri:** Writing – review & editing, Writing – original draft, Software, Methodology, Conceptualization. **Pietro Marco D'Angelo:** Writing – original draft, Visualization, Software. **Laura D'Orsi:** Writing – original draft, Visualization, Methodology. **Andrea De Gaetano:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Simona panunzi reports financial support was provided by Antonio Ruberti Institute of Systems Analysis and Computers National Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2024.104890.

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