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# SIMULATING VICTIM HEALTH STATE EVOLUTION FROM PHYSICAL AND CHEMICAL INJURIES IN MASS CASUALTY INCIDENTS

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**Abstract.** The field of discrete-event simulation for medical disaster management is relatively new. In such simulations, human victims are generated using pre-determined transitions from one health state to the next, based on a set of triggers that correspond to treatment or the clinical progression of untreated injuries or diseases. However, this approach does not account for subtle differences in clinical progression. We propose a parameter-based model to characterize the evolution of symptoms at first for physical and nerve agent chemical injuries. We used a Gompertz function to predict the time of death in trauma based on forensic data. Then we separately considered the effects of the chemical warfare agent sarin (GB) being the origin of the chemical injuries for the purpose of modelling a GB attack in a metro station. We emphasize that our approach can be extended to other CBRN threats pending knowledge of clinical progressions available in the literature for the purpose of casualty estimations. The intent is to provide an estimate of time to death without any treatment and overlay this model with a treatment model, improving the evolution of the health state. A modification for non-life-threatening injuries is included without losing generality. Improvement functions modelling medical treatment are proposed. We argue that the availability of injury scores vs mortality can greatly enhance the validity of the model.

**Keywords:** disaster medicine, discrete-event simulation, victim health state model, mass-casualty incidents, combined injuries.

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## Introduction

The objective of discrete-event simulation for mass-casualty incidents is to develop and optimize best practices for medical care, with the goal of saving as many victims as possible. In these simulations, the victims are the central component of the simulator logic. However, modelling the health state of victims is challenging due to the unpredictability of the clinical progression of injuries, particularly in severe cases, and the further deterioration of health when multiple injuries are present. Debacker et al. have proposed an approach in their SIMEDIS simulator, which considers predetermined clinical conditions for a database of 205 distinct victims who are classified as being critically, seriously, or lightly injured (Debacker et al., 2016; De Rouck et al., 2018). The clinical parameters, including blood pressure, pulse rate, respiratory rate, and motor response, are updated according to time. One limitation of this approach is that the health state is modified at discrete time intervals and doesn't consider dynamic changes in evolution (every change is scripted). Another limitation in this

database is that currently defined victims only sustain physical injuries as they were tailored for the specific case of an airport crash. Additionally, there is no interaction between predefined victims and their environment, such as exposure to chemical agents or new injuries. Other approaches to victim health states modeling involve the use of clinical databases of specific injuries from past conflicts (Bellamy, 1984). Analytical approaches have considered physiological systems separately (McDaniel et al., 2019) with a more granular point of view to a victim as a combination of subsystems. For the application of a mass-casualty simulator where victims are numerous (well over 500), such models were not considered for performance reasons. Casagrande also provides an interesting approach to victim health state modeling for injuries in the case of a nuclear detonation using data from the Time Task Treater Files (TTTF) (Casagrande et al., 2011) which have been established using the data from the Joint Trauma Registry System owned by the US Department of Defense (Holcomb et al., 2006). The TTTF contain specific patient codes with a list of tasks required to treat the victim allowing to estimate the total treatment time for specific injuries. To develop more realistic and dynamic victim profiles, a continuous health state model is flexible and convenient. Approaches to victim health state modeling are directly linked to physiological parameters modeling but focus on a single outcome, i.e., mortality. We decided to use a scoring system based on vital signs measured in routine prehospital care to characterize the victims' health states instead of modeling each victim's physiological system.

This study presents a continuous health state model that is incorporated into the SIMEDIS simulator. The model has been applied in a new scenario involving a GB attack in a metro station where a crowd movement occurs due to panic and in an artillery strike scenario in a rural area (Benhassine et al., 2022b). Therefore, the victims described can present both chemical and physical injuries, but the model can also be applied to blast injuries if knowledge about the outcome from these injuries can be inferred from data. Firstly, the model equations for the spontaneous evolution of physical and chemical injuries are presented with GB for the purpose of illustration. Secondly, we present treatment functions which aim at modelling the improvement on the health states. This work is an extension of the conference paper entitled "Continuous Victim Model for Use in Mass Casualty Incidents" presented at the 20th Industrial Simulation Conference ISC'2022 (Benhassine et al., 2022a). In this paper, more details are provided regarding the model equations, especially for the chemical injuries. It also presents the treatment functions which were not detailed originally.

A clinical parameter-based score is developed to characterize the health state of victims, which we call the SimedisScore (SS). The SS is calculated as an unweighted sum of five categories, each comprising five values ranging from 0 to 4, with lower values indicating worse health states. The categories consist of parameters that are routinely measured in prehospital medical care. These are the Glasgow Coma Scale, heart rate, respiratory rate, systolic blood pressure, and oxygen saturation (Sacco et al., 2008; Champion et al., 1989). To obtain the SS, Table 1 presents the corresponding value from each score. By summing the value for each of the five scores, one obtains a SS from 0 to 20. Subcategories of the first four parameters are based on existing trauma scores, while oxygen saturation categories are adapted from Raux et al. (2006). The inclusion of oxygen saturation allows for more detailed modeling of non-traumatic victims such as chemical injuries or respiratory disease. Military sources have

developed victim profiles for organophosphate chemical warfare agents that have been converted for use in simulation models by assigning a value for each score category based on descriptions provided in AMedP8(c) (Curling et al., 2010). For the SS to serve as a reference for victims' health states, a continuous evolution is required for both physical and chemical injuries.

**Table 1.** Overview of the components used in the SimedisScore, their categories and corresponding values

| Value | Glasgow Coma Scale | Oxygen Saturation | Heart rate | Systolic Blood Pressure | Respiratory Rate |
|---|---|---|---|---|---|
| 4 | >13 | 90–100% | 61–120 | >89 | 10–29 |
| 3 | 12–9 | 85–98% | ≥121 | 76–89 | >29 |
| 2 | 8–6 | 80–94% | 41–60 | 50–75 | 6–9 |
| 1 | 5–4 | <80% | 1–40 | 1–49 | 1–5 |
| 0 | 3 | 0 | 0 | 0 | 0 |

## 1. Physical injuries

There are three possible evolutions that can occur to a victim's health state: degradation, stabilization, or recovery. Additionally, one can define a decrease rate and a delay time after which the degradation starts. In 1825, Benjamin Gompertz proposed an exponential function to describe the mortality rate versus age (Gompertz, 1825). The Gompertz function G has the following form for the mortality versus age (here versus time):

$$G(t) = a\ \mathrm{e}^{-\mathrm{e}^{(b-ct)}}, \tag{1}$$

$a$ being an asymptotic value, $b$ being the shift in time and $c$ being the rate of decrease (if $c$ is negative). The Gompertz function will tend to 0 if both $b$ and $c$ are negative and to $a$ if $b$ and $c$ are positive. The Gompertz function was generalized by Ahuja and Nash (1967) and recently by El-Gohary (El-Gohary et al., 2013). In the latest reference, the generalization of the Gompertz function allows the definition of a survival function. Survival functions are widely used in the medical and biostatistical literature and allow for instance to characterize the outcome of treatments and is very macroscopic in nature (Dempsey & McCullagh, 2018). In the frame of the SIMEDIS simulator, the victim health state model is microscopic but needs to include a modification for victims with moderate or minor injuries to survive. Without this possibility, the function from Equation (1) can only represent a dying victim or a victim that keeps a constant SS value (which doesn't capture any degradation to the health state and would be less realistic).

The modification with the survival function is important to permit the victim to stay alive if, for instance, it has survivable injuries. It has the following definition (GG for Generalized Gompertz, renamed as the SS(t) function caused by physical injuries (hence the Phys. suffix):

$$GG(t) = SS_{Phys}(t) = a - \left(a - a\ \mathrm{e}^{-\mathrm{e}^{(b-ct)}}\right)^{\gamma}, \tag{2}$$

where γ is a positively defined shape parameter. We propose to use such a function as a basis for the victim health state evolution for trauma (conventionally referring to physical injuries). The victim death occurs when the $SS_{Phys}(t)$ function reaches 0. The maximum value of the function is 20 which corresponds to a fully healthy individual (a sum of the five physiological parameters set to 4 each). Figure 1 presents different combinations of parameters for the $SS_{Phys}(t)$ function.

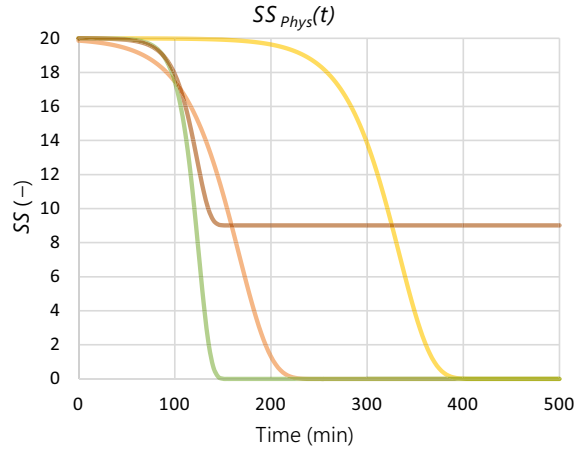


**Figure 1.** Example SimedisScore functions for physical injuries only ($SS_{Phys}(t)$). The following parameters were used (Equation (2)): yellow curve (a = 20; b = –10; c = –0.03; γ = 1); brown curve (a = 20; b = –10; c = –0.08; γ = 0.8); orange curve (a = 20; b = –5; c = –0.03; γ = 1); green curve (a = 20; b = –10; c = –0.08; γ = 1)

Analysis of the victim profiles created by Debacker et al. showed that clinical evolution of the SS in trauma victims follows an asymmetrical sigmoid function with a plateau phase followed by a progressively accelerating deterioration and a terminal deceleration (Debacker et al., 2016). From clinical experience, we often find a terminal compensatory effort of the human physiology in both trauma and non-traumatic patients. All these factors can be included in the proposed $SS_{Phys}(t)$ function. The choice of the Generalized Gompertz function was also motivated by its simplicity, only consisting of four variables, and *a* being a constant for this application. The link between the victim's age and the injuries is made via both the *b*, *c* and γ parameters. One can show that the $SS_{Phys}(t)$ function (when γ = 1) will approach zero at a time $t_{death}$ of approximately $(b–e)/c$ where *e* is Euler's number.

The $t_{death}$ is calculated based the Injury Severity score (ISS). The ISS is an injury severity score which links anatomical location and severity by means of the abbreviated injury scale (AIS) (Petridou & Antonopoulos, 2017)). The link between ISS and untreated time of death has historically been difficult to make as early treatment dramatically improves outcomes of critically injured victims, the time of injury and death are often not precisely known. The data reported in the literature is mostly based on post-mortem studies of road traffic accidents (Hussain et al., 2020; Raoof et al., 2019; Sahu et al., 2021; Clark et al., 2014), however Cros et al.also reported data from stab wounds, gunshot wounds, and blast injuries (Cros et al., 2013).

These studies suggest that ISS can be used to estimate an average survival time for severe traumatic injuries. We then extrapolated the data from these studies to fit an exponential survival time function. In Figure 2, we plot the available datapoints for ISS versus $t_{death}$ from the references along with the fit.

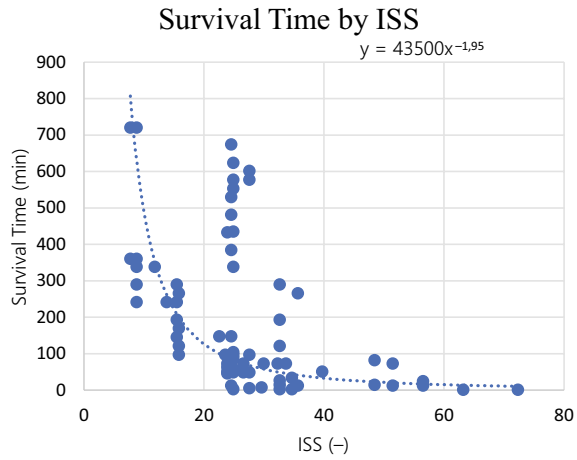


**Figure 2.** ISS of deceased victims and time of death (minutes) from Hussain et al. (2020), Raoof et al. (2019), Cros et al. (2013), Sahu et al. (2021). The fit is represented by the dotted line. It is noted that victims with an ISS of 25 are not well fitted by the equation and care must be taken in this case

$$t_{death} = 43500\ ISS^{(-1.95)}. \tag{3}$$

It should however be noted that there are severe limitations to this formula: there are no datapoints for low ISS numbers as mortality is typically very low and outside the scope of the studies linking ISS to time of death. There also is a big variation in the survival time of ISS between 25 and 36. We hypothesize that this is due to inaccuracies in the AIS reporting and the fact that ISS does not consider interaction between injuries and anatomical locations. For example: a single severe injury (AIS of 5) results in an ISS of 25 without regardless of its anatomical location, as well as a combination of 2 moderate injuries (AIS 3 and 4). While he latter is generally expected to survive a lot longer. The source of the data from Sahu is mainly post-mortem research on motor vehicle incident victims in rural regions. Rural prehospital care is frequently associated with long driving distances, and therefore represents better the untreated clinical evolution of a victim. A similar study by Cros et al. showed significantly higher survival times for homicide victims from stab wounds in the Paris region of France for 511 selected out of 4842 autopsy cases (Cros et al., 2013). The specific fitting values would need to be carefully revised in the case of available access to datasets from trauma patients, either in the form of a civilian database from hospitals' trauma centers or from military medical databases such as the Joint Trauma Registry System (Holcomb et al., 2006).

These datasets have little data on the lower ISS scores, because these are usually non-lethal. We assume victims with an ISS of less than 10 will survive at least 24 hours for the modeling duration. For those victims we assume a gradual decrease in SS over 60 minutes,

based on our internal database of expert opinion derived victim profiles, to a SS between 17 and 20 based on the victim's ISS.

To compensate for the victims age and decreased compensatory capacity, a bathtub curve is used to set c (faster decrease for children (age <12) and older people (age > 70) with a constant value in between). Consequently, all parameters are based only on age and ISS score. Additionally, victims with ISS higher than 25 have a faster decrease with a different bathtub curve parallel to the one for lower ISS values.

A last modification was introduced concerning mortality and injuries. Equation (3) estimates a "time of death" from the ISS resulting from a combination of injuries in a cumulative manner. Only a limited number of injuries are rapidly fatal such as major hemorrhage, tension pneumothorax, traumatic asphyxia or major cerebral injuries, but a combination of severe injuries resulting in high ISS scores does not generally lead to a quick death. To account for this effect, the γ parameter is only set to 1 if at least one lethal injury is present.

## 2. Chemical injuries

Equation (2) models the evolution of the victim's health state based only on physical injuries since the ISS (of Equation (3)) is defined for physical injuries. To consider chemical injuries, an additional term is added to Equation (2) depending on the inhaled dose of a toxic chemical agent (here GB as a test case).

$$SS_{Chem+Phys}(t) = SS_{Phys}(t) - \Delta Chem(t). \tag{4}$$

$\Delta Chem(t)$ being a function to be determined affecting the evolution of the health state of the victim after inhalation of an organophosphate chemical warfare agent. The effect of the chemical injury and physical injury are linearly combined in the health state. To define the chemical modification function, the AMedP-7.5 and the superseded AMedP-8(c) NATO standard progression of symptoms are used as a reference (North Atlantic Treaty Organization [NATO], 2018; Curling et al., 2010). The progression of symptoms for GB are provided for victims' total exposure ranges. Based on inhalational dose thresholds, the document categories clinical presentations of victims as "Injury Profiles" (IP). These are reported in Table 2.

**Table 2.** Reported symptoms and dose ranges for each GB Injury Profile (IP) derived from NATO (2018) and adapted from De Rouck et al. (2023)

| Injury Profile | Description |
|---|---|
| IP-1 | ■ Brief episode of ocular symptoms (pain and miosis) only.<br>■ Spontaneous recovery after 6 hours.<br>■ **Exposure range**: 0.2 to 1 mg min $m^{-3}$ |
| IP-2 | ■ Mild ocular and mild respiratory symptoms (wheeze and dyspnea)<br>■ Respiratory symptoms improve after 1.5 hours, and ocular symptoms improve after ±16h but linger for weeks.<br>■ **Exposure range**: 1 to 6.5 mg min $m^{-3}$ |

*End of Table 2*

| Injury Profile | Description |
|---|---|
| IP-3 | ■ Moderate intoxication with mild GI and respiratory symptoms.<br>■ These symptoms last about a week. Ocular symptoms persist longer.<br>■ **Exposure range**: 6.5 to 12 mg min $m^{-3}$ |
| IP-4 | ■ Moderate intoxication with severe bronchorrhea, respiratory distress and mild neurological impairment (agitation, anxiety, twitching, convulsions).<br>■ Improvement after 60–90 minutes, but mild ocular, respiratory and GI symptoms persist for days to weeks.<br>■ **Exposure range:** 12 to 25 mg min $m^{-3}$ |
| IP-5 | ■ Severe intoxication with respiratory insufficiency (central, muscular, and due to secretions), seizures and severe ocular and GI symptoms.<br>■ Brief seizures/coma (±15 minutes) but severe respiratory, muscular, and neurological symptoms persist for 1–2 hours, slowly improving over days to weeks.<br>■ **Exposure range:** 25 to 30 mg min $m^{-3}$ |
| IP-6 | ■ The most severe intoxication, where all symptoms are of the most severe category.<br>■ Death is expected after 15 minutes if untreated, due to a combination of flaccid paralysis, respiratory insufficiency, and status epilepticus/coma.<br>■ **Exposure range:** over 30 mg min $m^{-3}$ |

Originally, there were 6 different levels of intoxication for GB ranging for mild (IP-1 and IP-2) to moderate (IP-3 and IP-4), severe (IP-5) and very severe (IP-6). The application of these profiles was designed for the military population in mind for casualty estimation purposes following a GB attack. In essence, by adapting the exposure ranges with the methodology from De Rouck et al. (2023), one can apply the NATO model to the civilian population with a few assumptions and limitations in mind. The datapoints in Table 3 represents timestamps for which changes in SS are expected along with the magnitude of the change.

**Table 3.** Conversion of the clinical parameters of Table 2 into SS changes in the Δ*Chem*(*t*) function

| Time (min) | Δ*Chem* (IP-3) | Δ*Chem* (IP-4) | Δ*Chem* (IP-5) | Δ*Chem* (IP-6) |
|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 |
| 3 | 1 | 0 | 1 | 6 |
| 5 | 1 | 1 | 1 | 6 |
| 7 | 1 | 1 | 6 | 15 |
| 11 | 1 | 6 | 8 | 15 |
| 21 | 1 | 6 | 6 | 15* |
| 66 | 1 | 3 | 3 | 20 |
| 106 | 1 | 3 | 2 | 20 |
| 156 | 1 | 2 | 2 | 20 |
| 366 | 1 | 2 | 2 | 20 |
| 1006 | 1 | 2 | 1 | 20 |
| 1946 | 1 | 1 | 1 | 20 |
| 8646 | 1 | 1 | 1 | 20 |

*Note:* *Death is supposed to occur at this stage for 90% of victims belonging to this injury profile.

A fit is performed on the datapoints of 6 different chemical profiles depending on inhaled dose. The 4th and 5th injury profiles are well approximated by a modified $\chi^2$ distribution with the following mathematical expression (with the addition of a shape parameter $\gamma$).

$$\Delta Chem(t) = A + \left( \frac{\alpha}{2^{\frac{k}{2}}\Gamma\left(\frac{k}{2}\right)} t^{\left(\frac{k}{2}-1\right)} e^{-\beta\frac{t}{2}} \right)^{\gamma} . \quad (5)$$

A, $\alpha$, $\beta$, $k$ and $\gamma$ are AMedP-8(c) profile specific parameters determined by a least-squares fitting method. $\Gamma$ is the complex gamma function. In the original conference paper (Benhassine et al., 2022a), all profiles except IP-6 were fitted with Equation (5). Later it was realized that the first 2 profiles symptoms are mild enough as not to affect the SS and were neglected. For this reason, we propose to set a change in SS of 1 for the 3rd profile and use Equation (5) for the 4th and 5th profiles. The fitting parameters are provided in Table 4.

The justification for this simplification is that the first 2 profiles being not lethal will have no impact on mortality which is the main indicator in the simulator, but in other cases, in combination with physical trauma, victims can have a worsened health state due to an inhaled GB dose albeit non-lethal which can affect morbidity and mortality outcomes by shifting the time of death. Profile 6 (IP-6) is fitted with a Gompertz function (Equation (1)) with the following parameters (a = 20, b = 4; c = 0.48).

**Table 4.** Fitting parameters for each Injury Profile (IP) derived from Curling et al. (2010)

| | A | $\alpha$ | $\beta$ | $k$ | $\gamma$ |
|---|---|---|---|---|---|
| IP-4 | 3.35 | 10.2 | 1/90 | 2.17 | 1 |
| IP-5 | 1 | 21 | 1/40 | 1.45 | 0.8 |

The choice for Equation (5) has no justification beyond fitting purposes so we decided not to provide an interpretation of its parameters, but additional data can guide a more refined version in the future. Especially as careful validation is required if these profiles are to inform decision making processes linked to disaster management policymaking.

## 3. Treatment functions

The $SS_{Chem+Phys}$ function considers spontaneous evolution of injuries. The aim is to include the generated victims in a model of disaster response which is the goal of SIMEDIS. To address how the medical response interacts with the victims' health state progression, we decided to include 3 different types of modifications for treatment modeling. Victims with trauma need treatment to survive. To quantify the impact of treatment on the health state evolution, we propose that each treatment applied to a patient will modify its health state function when the treatment is applied and affect the health state after it has been finished.

There are three types of treatments that are implemented in the model:

- A life-saving treatment while the treatment is active (the victim will not die while this treatment is active).

- A positive effect treatment which wears off (medication, or injection).
- A life-saving treatment (permanent) such as a successful surgery.

Each treatment is applied to a single victim; thus, it is specific to a victim with its own $SS_{Chem+Phys}(t)$ function parameters. The specifics of the treatment function parameters depend on the skill level of the provider (doctor, nurse, paramedic, etc.), the location of the victim (type of treatment facility) and the specific treatment procedures. Discussions about these issues are out of scope of the current study which presents the basic equations only.

### 3.1. First treatment description

For the first treatment, we propose to adapt the $SS_{Chem+Phys}$ function as follows, while the treatment is being applied (where α is a treatment dependent parameter; for $t^*$ going from $t = t_0$ (start of treatment) until $t = t_1$ (treatment end) applied to victim $j$):

$$SS_{treatment1,Victim\ j}\left(t^*\right) = SS_{j,Chem+Phys}\left(t^* - t_0\right) + \sqrt{\alpha\left(treatment\right)\left(t^* - t_0\right)}\,. \tag{6}$$

During treatment, the victim cannot die, and treatment can either stabilize the *SS* or increase its value.

### 3.2. Second treatment description

For the second treatment, since the treatment will lose effectiveness with time, we propose the following adaptation to the $SS_{Chem+Phys}$ function:

$$SS_{treatment2,Victim\ j}\left(t^*\right) = SS_{j,Chem+Phys}\left(t^* - t_0\right) + e^{-\lambda\left(t-t_0\right)}\sqrt{\alpha\left(treatment\right)\left(t^* - t_0\right)}. \tag{7}$$

### 3.3. Third treatment description

The last treatment considers a successful life-saving intervention (LSI) and damage-control surgery. By modifying the γ parameter, the treatment prevents the victim from dying. Thus, the only difference with the untreated evolution is the parameter γ. From the start of the treatment, $t = t^*$ as the other treatments but when there is no "end" of the treatment, time keeps increasing until the end of the simulation and the victim continuously gets better and never dies. γ is a function of the treatment applied (the victim can recover faster with a more "powerful" effect of this treatment, so that γ is close to 0). With $0 < \gamma < 1$:

$$SimedisScore_{tr3,Victim\ j}\left(t^*\right) = a_j - \left(a_j - a_j e^{-e^{\left(b_j - c_j t^*\right)}}\right)^{\gamma\left(treatment\right)}. \tag{8}$$

## 4. Discussion and limitations

The presented victim model has numerous advantages for generating a large number of victims in the simulator, avoiding to manually create profiles and proving an all-hazards approach to injuries. It avoids frequent and computationally expensive database access for setting clinical progressions by using a set of dynamic equations versus time. The use of the ISS foregoes the complex nature of the physiological interactions in trauma. For instance,

a combination of injuries will provide an overall ISS, but this approach makes no distinction on the physiological system affected (e.g., cardiovascular, respiratory, or digestive system). However, the use of ISS as a basis has the major advantage that this data is widely collected and reported in trauma registries and is therefore readily available (O'Reilly et al., 2012).

The SS is defined as the sum of prehospital scores and the evolution of the SS, SS(t), depends on the age and ISS of the victim. This approach however does not incorporate the underlying mechanism of injury and potential intricate cross-effects between physiological parameters. There is latitude in the way that the parameters of the health state evolution are defined. $a$, $b$, $c$, $\gamma$, and the chemical injuries parameters are set as constants for each victim but could be replaced with functions, providing dynamic effects to be added. In order to achieve this more research and data is required.

There were no considerations regarding the route of exposure of the chemical agent and percutaneous exposure was neglected for GB, which might not be the case for other agents like VX and Novichok. Toxic doses inhaled following an explosion build up almost instantly versus slowly diffusing or evaporating sources. The model would need to be revisited for these considerations. The presented model is aimed at generating profiles which evolve versus time in the SIMEDIS simulator for the purpose of mortality estimation based on time evolution and treatment procedures.

## Conclusions

A dynamic health state progression model was developed for use in a computer simulator of mass casualty incidents. The idea was to create an alternative for injury definition and the generation victim clinical condition progression in computer modeling of mass casualty incidents, which is often very time consuming. We created a methodology to convert injuries into a combined resulting effect on the victims' physiological health state using existing prehospital scores as a basis for severity estimation.

A continuous model to describe the evolution of this health state in a mass casualty setting has been presented based on an existing dataset of clinical transitions for physical injuries and refined with the possibility to add chemical injuries to a set of physical injuries. The equation for physical injuries is based on a generalized Gompertz function. The parameters of this function are derived from the victim ISS and age. The contribution of chemical and physical injuries is linearly combined, and cross-interactions are neglected. Three treatment functions were presented to describe improvements in the SS(t) function, which in essence can drastically modify the mortality outcomes. We presented 3 types of treatment, one resulting in a monotonous improvement of the health state, and second one with a wearing-off effect and a third one, which permanently makes sure the victim remains alive. In reality, none of these outcomes are straightforward to assess, therefore we relegate the modeling of treatments to future studies pending real data.

## Future research

The presented model shows a generalization of the discrete-event victim model used in previous simulations where all victims had predetermined health state progressions set by

subject matter experts (Debacker et al., 2016; De Rouck et al., 2018). The flexibility of our new approach resides in the fact that hundreds or thousands of victims can be generated very quickly at simulation runtime, and in a very computer efficient manner (we calculated the average time to generate 468 victims to be 20.62 ± 1.56 seconds based on 10 replications on a single laptop equipped with an i9-12900H processor using 32Gb of ram). The adapted victim model is included in the current version of the SIMEDIS simulator and was already used in CBRN (Benhassine et al., 2022b) and battlefield scenarios. The presented model for chemical injuries only applies to one agent (GB) but data is accessible for other warfare agents and the same methodology could be applied. Radiological and nuclear changes (in the form of a ΔRad(t) function) to the SS are also integrated but were not presented here, because the timescale of health degradation is in units of days and not minutes/hours, which still needs to be implemented in SIMEDIS which was designed with initial disaster response in mind. Additional refinements could be inferred from access to trauma registries, both from civilian and military sources, to better estimate the empirical time of death estimation (Equation (3)). No specific physiological system was included at this time (cardiovascular vs respiratory or digestive systems), these would directly influence the dynamic evolution of the scores used in the definition of the SS score.

Future research possibilities are improving the quality of the assumptions used in the clinical evolution of treated and non-lethal victims and adding the interaction between the injured regions composing the ISS score.

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## Author contributions

MB wrote the manuscript. MB and RDR conceptualized the work. MDB, FVU, ED and IH supervised the work and reviewed the manuscript. FVU acquired the funding for this study.

MB and RDR have worked together on the publication and contributed equally.

## Disclosure statement

Authors declare this work voided of any competing financial, professional, or personal interests from other parties.

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