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Review

Extracting physiologic and clinical data from defibrillators for research purposes to improve treatment for patients in cardiac arrest

Trond Nordseth [a,b,c,*], **Trygve Eftestøl** [d], **Elisabete Aramendi** [e], **Jan Terje Kvaløy** [f], **Eirik Skogvoll** [a,b]

Abstract

Background: A defibrillator should be connected to all patients receiving cardiopulmonary resuscitation (CPR) to allow early defibrillation. The defibrillator will collect signal data such as the electrocardiogram (ECG), thoracic impedance and end-tidal CO_2, which allows for research on how patients demonstrate different responses to CPR. The aim of this review is to give an overview of methodological challenges and opportunities in using defibrillator data for research.

Methods: The successful collection of defibrillator files has several challenges. There is no scientific standard on how to store such data, which have resulted in several proprietary industrial solutions. The data needs to be exported to a software environment where signal filtering and classifications of ECG rhythms can be performed. This may be automated using different algorithms and artificial intelligence (AI). The patient can be classified being in ventricular fibrillation or -tachycardia, asystole, pulseless electrical activity or having obtained return of spontaneous circulation. How this dynamic response is time-dependent and related to covariates can be handled in several ways. These include Aalen's linear model, Weibull regression and joint models.

Conclusions: The vast amount of signal data from defibrillator represents promising opportunities for the use of AI and statistical analysis to assess patient response to CPR. This may provide an epidemiologic basis to improve resuscitation guidelines and give more individualized care. We suggest that an international working party is initiated to facilitate a discussion on how open formats for defibrillator data can be accomplished, that obligates industrial partners to further develop their current technological solutions.

Keywords: Cardiac arrest, Defibrillation, Advanced life support, Basic Life Support

Introduction

For patients in cardiac arrest, early cardiopulmonary resuscitation (CPR) and application of a defibrillator are both crucial for survival.[1] Modern defibrillators collect several types of continuous data from the patient, such as the electrocardiogram (ECG), thoracic impedance, end-tidal CO_2 ($EtCO_2$), blood pressure and pulse oximetry (SpO_2).[2–4] Some defibrillators also collect data from accelerometers to calculate chest compression depth and rate. These types of data offer great possibilities for research on how patients demonstrate different responses to resuscitation, including time-dependent effects of treatments given, such as intravenous drugs.[5–7] Any cardiac arrest situation will induce stress and disorder for the treatment team, making traditional collection of data challenging, especially in the early phase of resuscitation. Accurate time stamping of events, and giving a concise recall of these, may be biased by distorted memories among members of the treatment team. However, if a defibrillator is connected to the patient, and the data downloaded afterwards, a more accurate description of events is possible. For patients with out-of-hospital cardiac arrest, data recorded by automatic external defibrillators (AED) may give insights into events not possible to record by other means in this environment.

This type of research requires the systematic collection of data from defibrillators after each episode of cardiac arrest, and access to the raw data stored. Eftestøl and co-workers have given a thorough description of challenges caused by industrial proprietary file formats in defibrillator files, and several challenges in data handling.[8]

* Corresponding author at: Trond Nordseth, MD PhD, Department of Anesthesia and Intensive Care Medicine, St. Olav Hospital, NO-7006 Trondheim, Norway.

E-mail address: trond.nordseth@stolav.no (T. Nordseth).

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The vast amount of signal data possible to collect represents promising opportunities for the use of artificial intelligence (AI) and complex statistical analysis to assess systematically how patients respond to CPR.[9] This may provide an epidemiologic basis to improve resuscitation guidelines and to give more individualized care to patients in cardiac arrest.

The main aim of this review is to give an overview of current methodological challenges and opportunities in using defibrillator data for research purposes. This includes technical and logistic challenges in collecting defibrillator files, and making these available in open and uniform formats available for research. We aim to give an overview of how these data can be visualized and analysed with different signal processing, machine learning and statistical methods, and what clinical implications the results may have.

Methodological challenges

Retrospective analysis of episodes of cardiac arrest requires processing of large datasets to gather relevant clinical information. The defibrillator files need to be de-identified and linked to clinical information, most commonly available from Utstein-style templates and patient medical records.[10] This includes information on the EMS response, treatment provided in the pre- and in-hospital phase, and the patient's clinical response to CPR. Additional and more precise information, on relevant time intervals and types of events occurring, may be obtained by obtaining sound recordings during CPR.[11] Video recordings may be more challenging to obtain in this setting, but is possible by applying body-mounted cameras.[12] Another example is Valenzuela and co-workers, who analyzed security videos in a study of cardiac arrests occurring in Las Vegas casinos.[13] Multicenter studies may have a need to integrate data from several types of defibrillators, with specific and proprietary hardware and software characteristics that complicates data handling. A successful merging of defibrillator data and clinical data is key to any type of research on these types of data.[8] A typical workflow for collecting, storing, and analyzing data from defibrillators is demonstrated in Fig. 1.

Collection of defibrillator data

Defibrillators will usually store signal data and other types of data in a local file. Depending on the type of defibrillator, the files may be exported to a server wirelessly or be downloaded manually. There is no scientific or industrial standard on how to store or transfer these types of data, which have resulted in the development of several proprietary industrial file formats. The researcher is also confronted with several logistical challenges when collecting the files before they are lost. Some defibrillators generate a new file each time the defibrillator is turned on, which may make the distinction between files from real episodes and files with no relevant data difficult. In addition, real episodes may be overwritten due to limited memory in the defibrillator.

Access to raw data in defibrillator files

The exported files will contain the recorded biomedical signals that in different ways may reflect the physiological state of the patient. When information available in the ECG, thoracic impedance, $EtCO_2$, SpO_2 and blood pressure are combined, the severity of patient condition and whether the patient is deteriorating or improving physiologically may be assessed systematically.[5–7,14] The files may also include signals reflecting delivered therapy, such as acceleration and force signals from chest compression assist pads. Some defibrillators generate log files containing data on events such as power-on, attachment of pads, shock advisory analysis, defibrillation attempts, as well as time stamped information by clinicians using the device (e.g. the provision of intravenous drugs).

After the files have been collected, the data needs to be imported in a software environment suitable for analysis. Software such as SciPy, R, MATLAB (The Mathworks Inc., MA, USA) or similar are suitable for these purposes.[15,16] These provide opportunities for cutting edge research, including application of signal processing algorithms, statistical models and machine learning systems. However, data must be exported from a proprietary data format to file types that are readable, most commonly comma separated value (CSV) files. In some cases, data might be encoded in a binary format, which requires detailed knowledge of the encoding and the use of low-level functionality for decoding binary encoded information. What types of

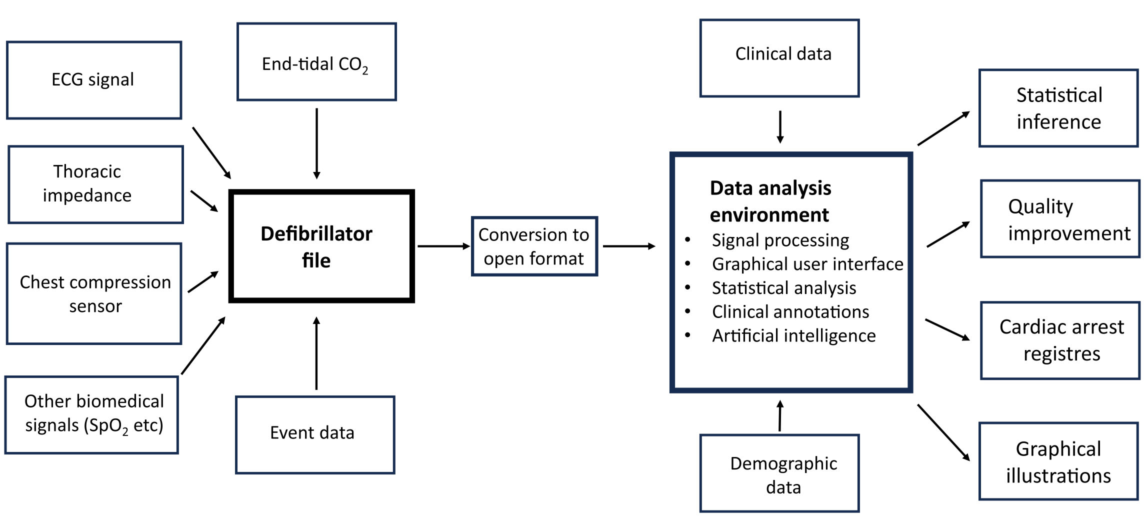

Fig. 1 – Overview of the workflow for collecting, storing, and analyzing data from defibrillators.

signals recorded, as well as how these are available through the different export solutions, will vary between manufacturers. Some manufacturers provide free export of high-quality data in an open format, whereas others offer expensive licensed solutions that need to be bought separately.

Visualizing and analysing signal data

The visualisation of various biomedical signals is an important part of the data exploration phase, where manual interpretations and classifications ("annotations") can be performed by clinicians. Although manufacturers of defibrillators provide software to handle and visualize signal data, these are specific for each type of defibrillator. One software solution that works well is the CODE-STAT for LIFEPAK defibrillators (Stryker, Kalamazoo, Michigan, United States).[17] Although these types of software can be used for research purposes, there are limited options for signal processing, manual annotations and integration of clinical information. We believe that overall data management is easier, and more options for data exploration and analysis are available, when researchers have access to the raw data. In our experience, such access is essential to enable the researcher to construct a complete timeline of the CPR episode.

A key part of the annotation process is to define what types of ECG rhythms are present at different points in time. As early as 1999, Sunde and co-workers demonstrated how logged event data, ECG and clinical data could be used to assess the quality of defibrillation and advanced life support given.[18] In this study, time intervals were determined automatically from the log files and time stamps of rhythm transitions and chest compression sequences which were annotated manually. An example of how defibrillator data can be visualized and annotated is demonstrated in Fig. 2 (the 'dataAnnotator', University of the Basque Country, Bilbao). A 30-seconds window of the different physiologic signals are shown in the upper three panels. Note the different rhythm intervals annotated along the complete timeline for the cardiac arrest episode in the bottom panel. Buttons for annotation and visualization purposes are visible in the left frame. This graphical user interface (GUI) has been developed with the software MATLAB, which provides a wide scope of tools for data analysis. The tools integrated in the 'dataAnnotator' need to be adapted to the specific characteristics of each defibrillator and the types of signals exported. A common challenge is that biomedical signals frequently are distorted by noise or interference signals, which negatively affects what type of information can be extracted for clinical interpretation. Pre-processing by filtering is crucial in most cases. This includes removing high-frequency noise in the ECG, removing CPR artefacts from the thoracic impedance and ECG, and extracting the ventilation component of the thoracic impedance.[19–25] Time alignment of the signals and matching with clinical time stamps are necessary to define the intervals of interest for the analysis. Signal processing techniques may require the representation of the signal in different domains, such as time or frequency. As different rhythms have their characteristic profiles, one might see how different therapies affects the frequency components.[26,27] Visualisation of relevant clinical information, such as when the patient received CPR, obtained return of spontaneous circulation (ROSC), was intubated or when any drugs was provided, may be central for the analysis. In some instances, it is not possible to make any meaningful assessment of ECG rhythm due to signal noise, and the researcher can either assume the previously annotated rhythm is present or define this portion of the signal as missing.

In general, the described methodology implies a post-hoc "reconstruction" of real-life events in a critical situation, based on sensor data and recorded clinical information of varying quality. Both signal data and clinical data can be missing or incomplete, and time stamping of events may be inaccurate due to different clock settings. In most instances it is unknown what type of ECG rhythm the patient had before the defibrillator was attached. Signals showing start of chest compressions will commonly be assessed as the start of the cardiac arrest episode, although the patient may have been in a state of severe circulatory shock, or in cardiac arrest, for seconds or minutes before CPR is started. The classification of the patient being in cardiac arrest or not will mainly *reflect decisions* made by the treatment team to start or to stop CPR. Thus, any analysis on these types of data should be done with several precautions in mind.

Classification of data from episodes of CPR

Based on the ECG and other information, the patient is commonly classified being in ventricular fibrillation or -tachycardia (VF/VT), asystole, pulseless electrical activity (PEA), having obtained return of spontaneous circulation (ROSC) or having been declared dead.[7,28,29] Thus, a five-state model for mutually exclusive clinical states can be considered, demonstrated in Fig. 3. The event of death being declared should be based on clinical data. The decision to withhold CPR efforts may be based on patient comorbidity and underlying prognosis and may be independent of any patient response to CPR. A demonstration of highly different trajectories in 20 patients with cardiac arrest is given in Fig. 4A. A continuous demonstration of the prevalence of the different states can be given with 'prevalence plots', as demonstrated for the same 20 patients in Fig. 4B. These types of figures may be generated with the R-package "TraMineR".[30]

Distinguishing between PEA and ROSC may be challenging and depends on what type of clinical information is available. Time stamping of ROSC in paper records or in the defibrillator may be recorded by personnel on scene, but are often absent, inaccurate, or unreliable. A pause of > 1 minute in chest compressions, the presence of an organized ECG rhythm and documentation of ROSC in the paper records, can be used retrospectively to classify that ROSC was likely present.[31] Increasing $EtCO_2$ values may identify ROSC but requires that the defibrillator has this capability. The "cut-off" value to define ROSC based on $EtCO_2$ is uncertain and debated.[32] Currently, the European Resuscitation Council (ERC) guidelines state that "*an increase in ETCO2 during CPR may indicate that ROSC has occurred*" and that "*no specific threshold for the increase in end-tidal CO2 has been identified for reliable diagnosis of ROSC*".[28]

Distinguishing between "fine VF" and asystole may be difficult, and the classification may be based on discerning signal amplitude details measured in millivolts. The width and rate of QRS complexes may also yield information. In PEA, decreasing QRS-width and increasing heart rate have been shown to be predictive of ROSC being likely to occur in the following minutes.[33,34] The quality of CPR is commonly assessed by chest compressions and ventilations given, based on CPR assist pad acceleration signals (compressions), cyclic variations in the thoracic impedance (compressions and ventilations) and in the capnography (ventilations).[35–40] These can be used to characterize chest compression depth, rate and duty-cycle, as well as ventilation rate, duration, amplitude of inhalation / exhalation and levels of $EtCO_2$.[24,38] Although resuscitation

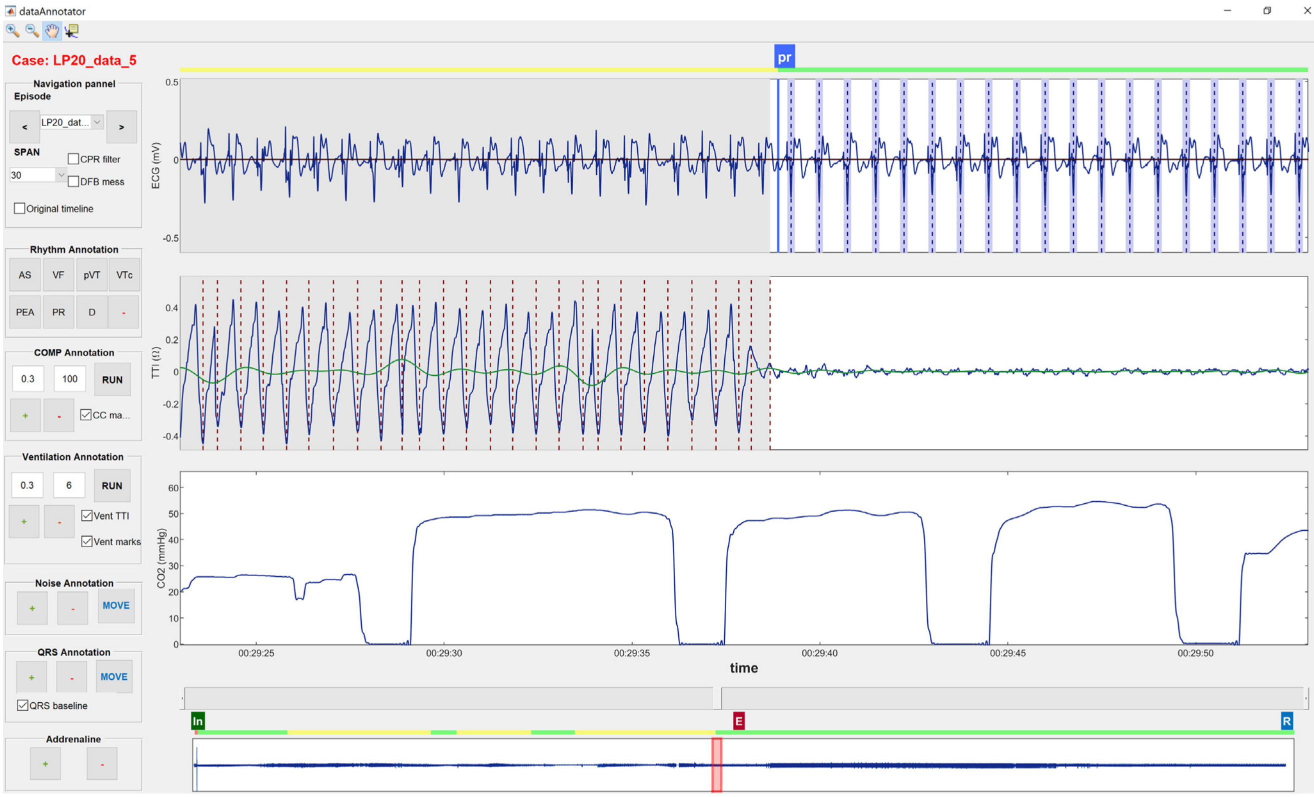

Fig. 2 – An example of data analysis with the 'dataAnnotator' (University of the Basque Country, Bilbao), programmed in MATLAB. The upper panel is the ECG, the second panel contains the thoracic impedance signal, and the third panel contains the end-tidal CO_2-signal. A 30-seconds window is shown, where a first interval with chest compressions is observed followed by a second interval with a pulse generating rhythm (annotated as PR). The sequence of rhythm changes is plotted as a bar in the bottom panel for the complete episode of one hour, where color-coded rhythm intervals are visible (yellow: PEA, green: PR). The 30-second window shown in the upper panels is highlighted as red in the bottom panel.

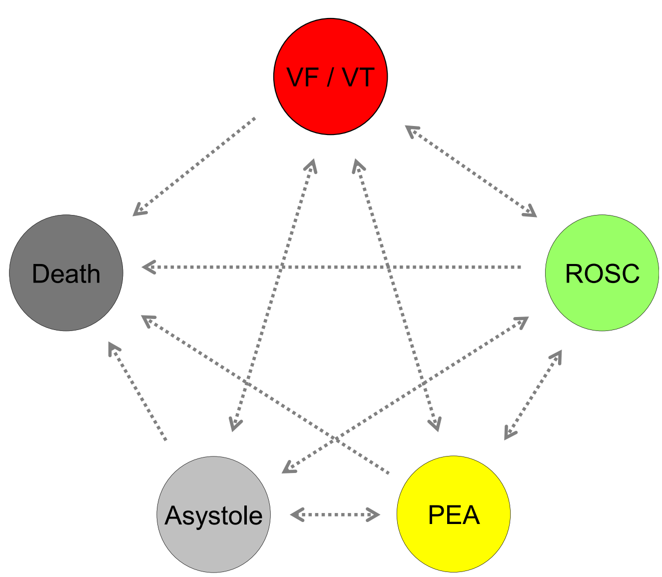

Fig. 3 – Multistate model in resuscitation research. VF/VT – ventricular fibrillation or -tachycardia. PEA – pulseless electrical activity. ROSC – return of spontaneous circulation.

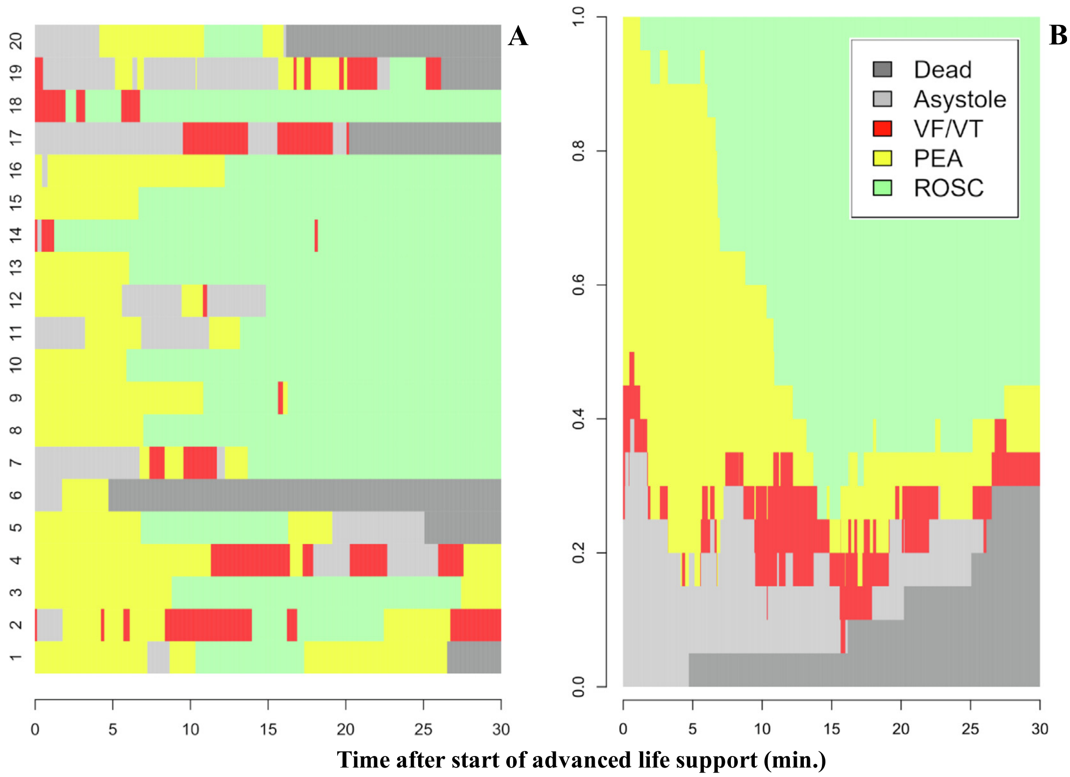

Fig. 4 – Plot of individual sequences of state changes in 20 patients receiving advanced life support can be seen in panel A. The corresponding state prevalence can be seen in panel B. The figures have been generated with the R-package "TraMineR". VF/VT – ventricular fibrillation or -tachycardia. PEA – pulseless electrical activity. ROSC – return of spontaneous circulation.

guidelines have specific recommendations on CPR quality, the methods to compute the metrics have been sparsely described, except by Kramer-Johansen and co-workers.[41]

The classification of ECG rhythms and other events may also be automated by using computer algorithms. Such algorithms have been developed by industrial corporations and research groups, although few are openly available. The cardiac arrest rhythms differ significantly from ECG rhythms observed in hemodynamically stable patients, making most of the classical algorithms for QRS detection or ECG segmentation unsuitable. The signals are characterized by waveform time and frequency characteristics that change rapidly, influenced by the physiologic state of the patient and treatments given during CPR. In addition, the classification is usually performed in short intervals (<5–10 seconds) when chest compressions are paused. Analysis of the ventricular fibrillation waveform has been used to predict the outcome of defibrillation.[42–47] The probability of ROSC (pROSC) can be monitored from VF segments throughout the resuscitation episode.[27,43] This has been applied to study how the VF waveform reduces pROSC during pauses after interruptions of chest compressions and increases pROSC after longer sequences of chest compressions.[26,48] Other studies have focused on classifying other cardiac rhythms occurring during resuscitation.[49–51] Several techniques permit analysing the ECG even when distorted by chest compressions. These integrate advanced filtering techniques (multistage, adaptive etc.) in combination with ad-hoc post-filtering rhythm classification algorithms, some based on machine learning.[21,25,52,53] Automated algorithms can assist in defining the time of ROSC using the ECG, thoracic impedance or capnography.[54–56] Even more, recent proposals provide solutions to accurately annotate regular rhythms, both pulsed and pulseless, even when signal intervals are short.[57,58]

Statistical analysis

After the data has been visualized and annotated, a coherent timeline has been established and statistical modelling can start. The modelling needs to take the time aspect into account.[33] Typical goals of the analysis are to try to understand and quantify factors of importance for patient outcomes, or to predict these outcomes. The ultimate outcome is whether the patient survive to hospital discharge. Thus, the goal is to understand and quantify the processes leading to this, such that future management can be optimized to improve patient outcomes. In resuscitation from cardiac arrest, treatment is intimately related to the condition of the patient. Knowing the order of interventions and subsequent observations may thus allow for reasoning about cause and effect. It is therefore of interest to model the state of the patient along the timeline, or study sub-parts of the process, for instance shock success in VF/VT. However, the data are of very different nature which require different modelling approaches.

Predictor variable categories

Predictor variables, also called explanatory variables, independent variables or features, are commonly termed 'covariates'. These have characteristics that require different approaches when linking them to the outcome variables, demonstrated in Table 1. *Time fixed predictor variables* have the same value through the entire patient trajectory, are easy to handle and can be used in any regression model and

Table 1 – Predictor variables relevant for statistical analysis of clinical data and data collected by defibrillators.

Type of predictor variable	Examples	Statistical model	Modifiable at any level?
Patient fixed (determined by the patient)	Age, sex, previous medical history	Regression methods, time-to-event models	No.
Situation fixed (determined from the outset depending on the circumstances)	Location in- or out-of-hospital, likely diagnosis and immediate cause (e.g., drowning), presenting rhythm, bystander efforts, emergency response time, availability of biochemical and imaging results	Regression methods, time-to-event models	To some degree, at the population or hospital level (bystander CPR, emergency team response time, defibrillator available).
Treatment time varying (Treatment that is changed experimentally and/or in response to clinical development)	DC shock in VF, CPR quality metrics, medication, modified CPR methods (e.g., active compression- decompression)	Time-to-event models with time-dependent predictor variables, joint models.	Potentially, in the individual patient (e.g., anti-arrhythmic drug in refractory VF).
Patient time varying (Changing over the course of resuscitation)	Clinical state of the patient (asystole, VF, PEA, temporary ROSC). ECG characteristics like QRS rate and width, and AMSA in VF. Direct or surrogate measures of coronary perfusion (e.g., blood pressure).	Longitudinal regression models, Multistate time-to-event, joint models.	No. These are biomarkers that reflect the patient's condition; and may alternatively be considered intermediate outcomes.
Patient dynamic (summarizing the process until present)	Time spent in the clinical states. Identifies the personal trait; a "frailty" equivalent.	Additive time-to-event model	No, past events cannot be altered.

most time-to-event models. *Time dependent predictor variables* change values over time, and their path may possibly be related to the process observed. These require more careful handling if they are of the endogenous (or internal) type, i.e., their path is known to be related to the process observed. *Dynamic predictor variables* are variables containing information about the past of the process, e.g. elements of the transition history such as the time already spent in a given state.[59,60]

Time to event models

It is crucial to incorporate the time aspect of the resuscitation process in the statistical analyses, and thus using various time-to-event models are natural approaches. These can range from simple single event models that study transitions from one clinical state to another, to complex models aiming to grasp the entire patient trajectory. A multistate model allows one to model the entire path of the state of the patient from the start of resuscitation until sustained ROSC has been obtained or death been declared, as demonstrated in Figs. 3 and 4.[5,7,31,61,62,63] These models take the issue of "competing risks" into account, as a patient with ROSC can transition to the states of PEA, asystole and VF/VT. To study the impact of predictor variables on simple "from-to" transitions, for instance the impact of initial rhythm on the transition from PEA to ROSC, classical survival analysis models like the Cox proportional hazards model or Aalen's linear model are natural choices.[64–66] A benefit of using Aalen's linear model, compared to the Cox proportional hazards model, is the ability to handle dynamic predictors and to study direct and indirect effects.[59,60] A drawback with the non-parametric Aalen model is that it models the *cumulative intensity*, which is rather intricate to interpret. In this respect the semi-parametric Cox model is better, and completely parametric approaches like Weibull regression or accelerated failure time models can be easier to understand.[67,68] When including important time-dependent predictor variables in time-to-event models there are several challenges. These include noise, partly missing data and that these are internal predictor variables. For proper handling of such issues, joint models have emerged as a very useful approach.[34,69]

Discussion

The systematic use of data from defibrillators to assess patient response to CPR is a promising field of research. However, there are several challenges in data collection and handling that should be addressed by the resuscitation community. So far, defibrillator data have been stored in industrial proprietary formats not primarily designed for research. Low quality data with limited access will continue to be a barrier to research. This is a paradox given that emergency medical services (EMS), hospitals, universities and the patients themselves should have the main ownership to the raw data, according to principles in the European Union General Data Protection Regulation (EU GDPR).[70] Recital 4 in this regulation also states that "*the processing of personal data should be designed to serve mankind*". Thus, there is a need for better incentives and organizational demands on manufacturers of defibrillators to improve their solutions to make data openly available for research.

The use of data from defibrillators, and other types of electronic recordings from real life critical events (e.g. voice, video), comes with some ethical challenges. As the defibrillator will record possible wrong judgements, such as failure to shock VF, or inappropriate sequences of actions compared to guideline recommendations, the data need to be handled in a responsible way. Defibrillator data combined with voice- or video recordings of emergency personnel and bystanders, under severe psychological stress, may be used in a way that are not in their best interest in media coverages and legal processes.

Clinical trials that include patients with cardiac arrest should consider systematic collection of defibrillator data as part of the study setup. This will allow for better control of timelines and the events occurring during CPR. However, this type of data collection and analysis is very resource demanding, and the costs versus benefits must be considered. Defibrillator files should also be considered collected and integrated with cardiac arrest registries, which will allow automatic registration of information that is entered manually today.[8,71] The integration of defibrillator files into the resuscitation registries would also allow the release of the further potential of AI based models requiring larger data sets. This will allow for analysis and statistical modelling on much larger data sets and allow for comparison of results from different EMS systems and hospitals. Increased use of automatic registrations and annotations will increase both internal and external validity.

To assess potential relationships between therapies given and patient response during CPR, studies need to be designed such that appropriate data from defibrillators are collected and specific events during resuscitation are meticulously recorded. If causal relationships can be established at different phases of resuscitation, the covariates can be altered by the CPR team and the clinical course of the individual patient can be turned in a more beneficial direction. Such covariates are found among the *patient time varying* variables, such as the current clinical state of the patient. If observed reliably, this may inform and guide on the *treatment time varying variables*. A simple example is immediate defibrillation in VF without delay. However, such a simple approach is less clear for the other clinical states. If the QRS rate in PEA is slowing down and the QRS complex is widening, this can be indicative of resuscitation efforts going in the wrong direction. What the proper response should be is less clear. The treatment team can administer adrenaline, increase compression depth, administer intravenous fluids, increase ventilation and more. The individual effects of these measures on the patient trajectory are mainly unknown, except for adrenaline which increases the probability of ROSC and the heart rate both in surviving and non-surviving patients.[5,6,72]

Given that the individual *patient fixed* predictor variables are of major importance, a possible approach to future research would be to consider systems of mixed effects stochastic differential equations, which incorporates system dynamics, individual traits, and stochastic components.[73,74] Another future approach could be exploring and adapting suitable state space models.[75] A better understanding of the individual effects of treatments on patient trajectories may lead to better guidelines for resuscitation, and the opportunity for more tailored care based on each patient's clinical response.

We believe that we have brought forward several sound arguments to develop more uniform and open data formats for defibrillator data, that make these easily accessible for researchers and clinicians. There is a need for a broader initiative by the resuscitation community to accomplish this. We suggest that an International Liaison Committee (ILCOR) working party is initiated to facilitate a broad discussion on how more open and accessible formats for defibrillator data can be accomplished, in a way that obligates industrial partners to further develop their current technological solutions.

CRediT authorship contribution statement

Trond Nordseth: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Conceptualization. **Trygve Eftestøl:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Elisabete Aramendi:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology. **Jan Terje Kvaløy:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Eirik Skogvoll:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization.

Declaration of competing interest

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

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Author details

[a]*Department of Anesthesia and Intensive Care Medicine. St. Olav Hospital, NO-7006 Trondheim, Norway* [b]*Department of Circulation and Medical Imaging, Faculty of Medicine, Norwegian University of Science and Technology, NO-7491 Trondheim, Norway*[c]*Department of Research and Development, Division of Emergencies and Critical Care, Oslo University Hospital, Oslo, Norway* [d]*Department of Electrical Engineering and Computer Science, University of Stavanger, NO-4036 Stavanger, Norway* [e]*Department of Communication Engineering, University of the Basque Country, Bilbao, Spain* [f]*Department of Mathematics and Physics, University of Stavanger, NO-4036 Stavanger, Norway*

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