Available online at www.sciencedirect.com

Resuscitation Plus

journal homepage: www.elsevier.com/locate/resuscitation-plus

Review

Artificial intelligence to support out-of-hospital cardiac arrest care: A scoping review

Jake Toy[a,b,c,e,*], *Nichole Bosson*[b,c,e], *Shira Schlesinger*[b,e], *Marianne Gausche-Hill*[b,c,e], *Samuel Stratton*[a,d]

Abstract

Background: Artificial intelligence (AI) has demonstrated significant potential in supporting emergency medical services personnel during out-of-hospital cardiac arrest (OHCA) care; however, the extent of research evaluating this topic is unknown. This scoping review examines the breadth of literature on the application of AI in early OHCA care.

Methods: We conducted a search of PubMed®, Embase, and Web of Science in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews guidelines. Articles focused on non-traumatic OHCA and published prior to January 18th, 2023 were included. Studies were excluded if they did not use an AI intervention (including machine learning, deep learning, or natural language processing), or did not utilize data from the prehospital phase of care.

Results: Of 173 unique articles identified, 54 (31%) were included after screening. Of these studies, 15 (28%) were from the year 2022 and with an increasing trend annually starting in 2019. The majority were carried out by multinational collaborations (20/54, 38%) with additional studies from the United States (10/54, 19%), Korea (5/54, 10%), and Spain (3/54, 6%). Studies were classified into three major categories including ECG waveform classification and outcome prediction (24/54, 44%), early dispatch-level detection and outcome prediction (7/54, 13%), return of spontaneous circulation and survival outcome prediction (15/54, 20%), and other (9/54, 16%). All but one study had a retrospective design.

Conclusions: A small but growing body of literature exists describing the use of AI to augment early OHCA care.

Keywords: Out-of-hospital cardiac arrest, Prehospital care, Emergency medical services, Medical dispatch, Artificial intelligence, Machine learning, Deep learning

Introduction

Over 250,000 people are treated by emergency medical services (EMS) for out-of-hospital cardiac arrest (OHCA) annually in the United States.[1] While the incidence of successful prehospital return of spontaneous circulation (ROSC) has been reported at approximately 27%, the chances of survival are low at around 9% and 7% for survival to hospital discharge and neurologically intact survival, respectively.[1] Despite significant research into prehospital resuscitation, survival outcomes after OHCA have remained low.[2]

The role of artificial intelligence (AI), including machine learning (ML), deep learning (DL), and natural language processing (NLP), as decision-support for EMS personnel in the management of OHCA is rapidly evolving. In the dynamic out-of-hospital setting where critical management decisions must be based off limited information, AI may assist EMS clinicians in quickly and objectively synthesizing patient data to guide care. Prior studies have demonstrated the feasibility of AI in assisting dispatchers in the early recognition of OHCA, and EMS clinicians and emergency department (ED) physicians in OHCA prognostication based solely on prehospital factors. To date, little research has evaluated the literature scope pertaining to the use of AI in emergency care[3] and in cardiac arrest care[4,5], and no studies have mapped the extent of literature on the use of AI as decision-support in the prehospital OHCA management.

We aimed to perform a scoping review on the use of AI as decision-support for OHCA management in the prehospital and early phases of care. The intent of this review is to inform EMS clinicians, physicians, and researchers on the current scope of literature on the use of AI as decision-support in early OHCA care.

* Corresponding author at: Los Angeles County EMS Agency, 10100 Pioneer Blvd, Santa Fe Springs, CA 90670, USA.
E-mail addresses: jake.toy@gmail.com, jtoy2@dhs.lacounty.gov (J. Toy).

https://doi.org/10.1016/j.resplu.2023.100491
Received 12 June 2023; Received in revised form 23 September 2023; Accepted 11 October 2023

Methods

We performed a search of peer-reviewed articles indexed in Embase, PubMed®, and Web of Science on January 18th, 2023. Articles published up to the search date were eligible for inclusion. Key search terms included 'artificial intelligence', 'machine learning', 'deep learning', 'natural language processing', and 'out-of-hospital cardiac arrest' (Fig. 1). After removal of duplicate publications, a single investigator (J.T.) who is an emergency medicine physician specializing in EMS screened titles and abstracts for relevancy based on predefined criterion (Supplementary Fig. 1). Selected articles underwent full-text screening. We conducted this review in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews guidelines (See Fig. 2 for PRISMA checklist).[6]

Studies were included if they used subsets of AI including ML, DL, or NLP as decision-support in the early phases of non-traumatic OHCA care. ML requires the input of structured data and learns in a supervised or unsupervised manner to make predictions. DL, a subset of ML, automatically inputs structured or raw data into multiple layers known as neural networks to organize and classify information and output predictions. Both ML and DL frameworks utilize classification algorithms of varying complexity (i.e., random forest, convolutional neural networks) to recognize, understand, and group data elements into categories which can then be interpreted by a human operator. NLP refers to the ability of a computer to understand and interpret text or spoken human language.

The search focused on peer-reviewed, primary studies published in academic journals. Studies were restricted to those published in the English language and based on human subject research. Studies were excluded if they did not restrict the patient population to non-traumatic OHCA, did not include ML, DL, and/or NLP as the AI intervention, or did not utilize input data from the prehospital setting or data obtained immediately upon arrival to the ED. Of note, studies utilizing non-prehospital data that are applicable and could be easily collected in the prehospital setting were included (i.e., electrocardiogram [ECG] waveform data). Conference abstracts, review articles, editorials, and gray literature were excluded.

Studies were filed into the citation-manager Zotero (Version 6.0.23; Corporation for Digital Scholarship, Vienna, Virginia, USA) and data were extracted by a single investigator (J.T.) into an Excel spreadsheet (Version 16.66.1; Microsoft Corp, Redmond Washington, USA). We extracted year, country of origin, AI branch (i.e., ML, DL, or NLP), classification algorithm (i.e., random forest, support vector machine), number of input predictors, data input type (i.e., clinical variables, ECG segment), database used, database size, and primary study outcomes. Country of origin was defined as the country were the authors declared their institutional affiliation. The category 'Multinational Collaboration' was created for studies with authors from two or more countries. We summarized descriptive statistics as frequencies and percentages. No personal or individual identifiers of human study subjects was retrieved in this literature review.

Results

The initial search yielded 318 total articles (Fig. 2). After removal of duplicate publications, 173 articles remained. After screening of titles and abstracts, 99 articles remained. Full manuscript review yielded 54 (31%) articles for inclusion.

Overall study characteristics

Of 54 included studies (Fig. 3), 15 (28%) were from the year 2022 and there was an annual increase in publications starting in 2019. The majority of studies were carried out by multinational collaborations (20/54, 38%), with additional studies from the United States (10/54, 19%), Korea (5/54, 10%), and Spain (3/54, 6%). We classified studies into four main categories based on their use of AI including ECG waveform classification and outcome prediction (24/54, 44%), early dispatch-level detection and outcome prediction (7/54, 13%), return of spontaneous circulation (ROSC) and/or survival outcome prediction (15/54, 20%), and other uses (9/54, 16%). All studies had a retrospective design except one by Blomberg et al.[7] See Table 3 for study list.

ROSC and survival outcome prediction

Fifteen studies were identified that used AI for ROSC and survival outcome prediction (Table 1). The majority were from 2022 (5/15, 34%)[8–12] and all but one were published in the past five years. Most studies were carried out by multinational collaborations (4/15, 27%)[12–15] and from Korea (3/15, 20%)[16–18], Japan (2/15, 14%)[9,19],

Inclusion Criteria	Exclusion Criteria
Studies focused on non-traumatic OHCA care and machine learning, deep learning, or natural language processing as the intervention	Studies not focused on non-traumatic OHCA as the target population
Studies focused primarily on the prehospital phase of care (i.e. dispatch-level, field care)	Studies without machine learning, deep learning, or natural language processing as the intervention
Peer-reviewed publications	Not focused on the early phase of care (e.g. studies based in the intensive care unit)
Primary studies	Reviews, editorials, conference abstracts
	Not printed primarily in English

Fig. 1 – Inclusion/exclusion criteria.

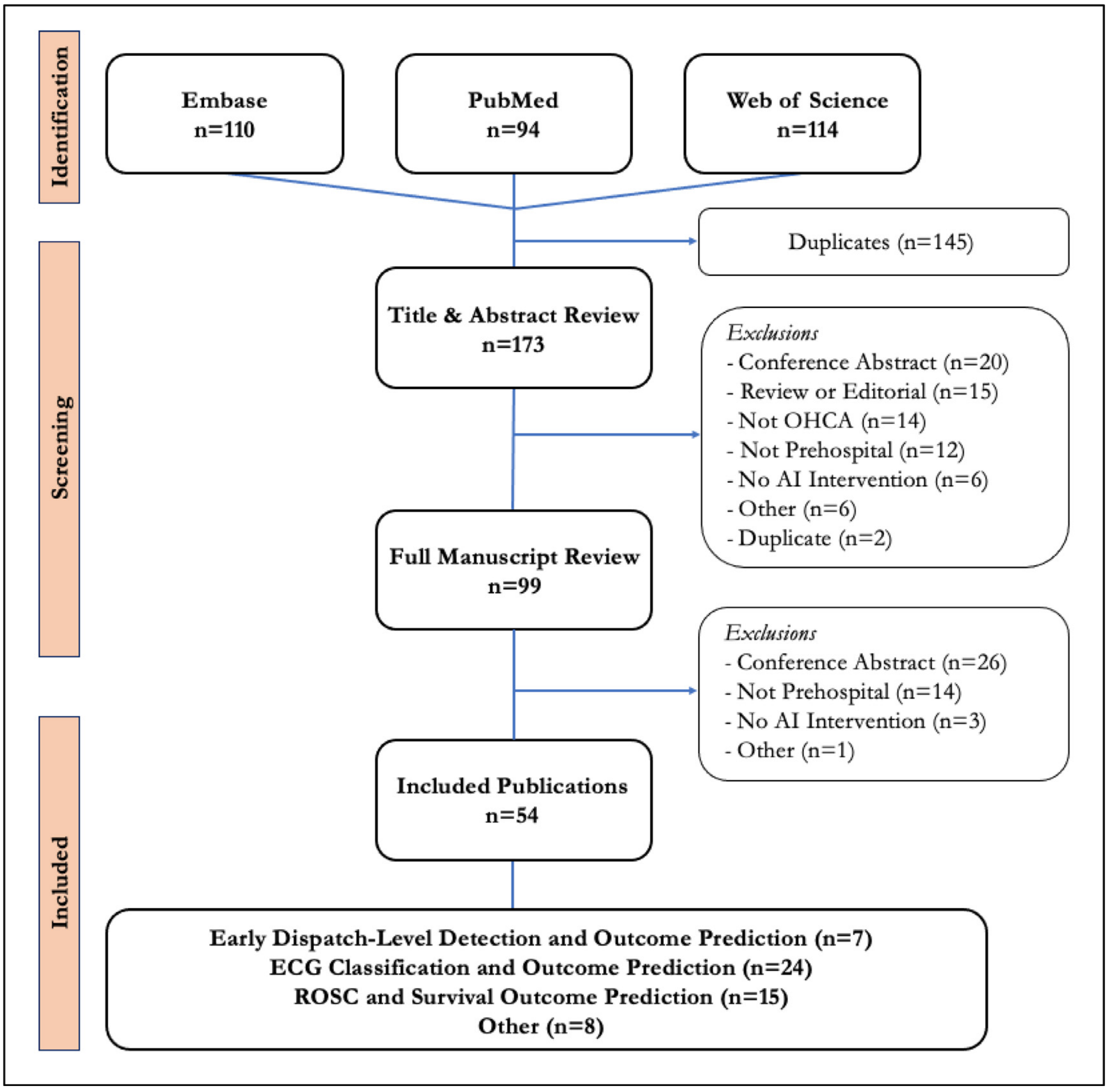

Fig. 2 – Selection Flow Chart. AI = artificial intelligence, ECG = electrocardiogram, OHCA = out of hospital cardiac arrest, ROSC = return of spontaneous circulation.

and the United States (2/15, 14%)[8,20]. Eleven studies (73%) focused on survival prediction[8–11,13,14,17–21], two studies (13%) focused on ROSC prediction[12,15], and two studies (13%) focused on both[16,22]. Most studies excluded patients < 18 years of age or did not specify an age cutoff, while a single study by Al-Dury et al.[13] explicitly included both adults and children. The number of patients included in each study ranged from 194 to 170,678 with the majority of studies including > 5,000 patients from large OHCA databases.

Among studies with models aimed at predicting survival and/or ROSC, eleven utilized ML[9–11,13–15,17,19,21–23] and four used both ML and DL[8,16,18,20]. All of these studies utilized a random forest classification algorithm as one type of the ML classification algorithms and additional ML and DL classification methods included logistic regression[8,9,16,18–21], support vector machine[9,18–20,22], k-nearest neighbor[8,9,16,20,22], decision tree[8,9,16,20], light gradient boosted machine (LightGBM)[8,9,14,20], extreme gradient boosting (XGboost)[8,9,17,20], multilayer perceptron[18,19,21], Autoscore[10,15], deep neural networks[8,20], embedded fully convolutional network[8,20], gradient boosting[8,20], artificial neural networks[14], classification and regression tree[11], Lagrangian support vector machine[16], naïve bayes[22], neural networks[22], reduced support vector machine[16], regularized logistic regression[17], and voting classifier[17]. All studies utilized more than one classification algorithm with the exception of one study by Liu et al.[15] which used a single ML classification algorithm (random forest) and compared it to an existing prediction score.

The number of predictors utilized in the various classification algorithms employed by each study to predict ROSC and survival ranged from three to 27 with an overall mean of 14.7 (Fig. 4). In these studies, 12 of 15 models[8–10,12,13,15–17,19–22] utilized only predictors from the prehospital setting, while the remaining three models[12,14,18] also incorporated one to two predictor variables obtained upon ED arrival including initial ED vitals, initial ED ECG, consciousness level upon ED arrival, and time from ED arrival to ROSC.

Early dispatch-level detection and outcome prediction

Seven studies were identified that used AI for the early detection of OHCA and outcome prediction at the dispatch-level from audio-based input (Table 2). All were published in the past five years. The studies were conducted by investigators in multinational collaborations (2/7, 29%)[22,28], France (2/7, 29%)[24,25], with additional

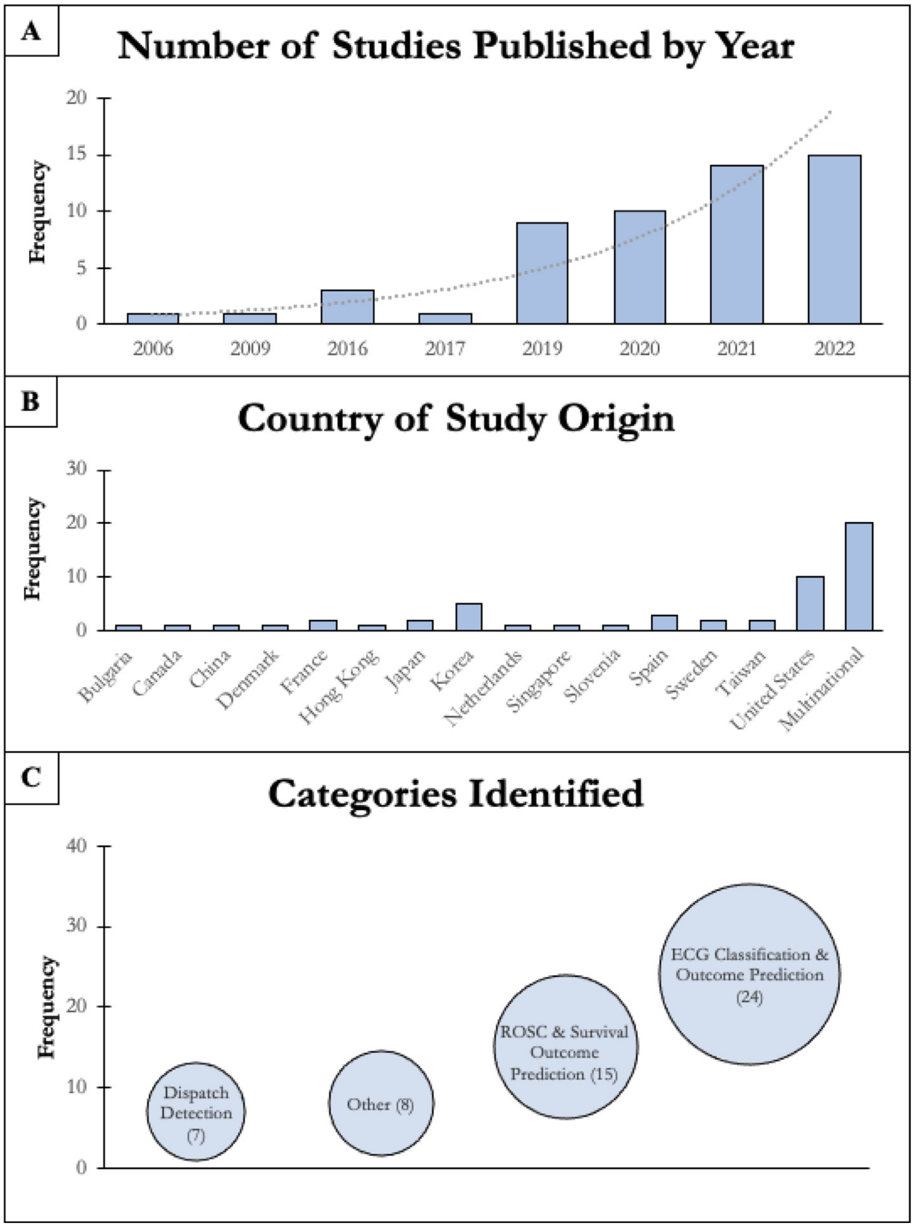

Fig. 3 – Characteristics of all included studies in this scoping review. *A) Studies from the year 2023 were omitted. ECG = electrocardiogram; ROSC = return of spontaneous circulation.

studies from Denmark[26], Sweden[27], and Taiwan[28]. Four studies[7,26,27,29] focused on the early detection of OHCA based on linguistic (e.g., spoken words) features in the dispatch-call audio while Rafi et al.[24] focused on the phonetic (e.g., vocal acoustic characteristics) features of the callers voice in the dispatch-call audio. Chin et al.[28] characterized callers' emotional state during dispatch calls for OHCA and Arcolezi et al.[25] predicted the need for transport and mortality outcomes from the dispatch call audio. The exact number and types of inputted predictors varied greatly and/or were not well described in these studies. One study by Blomberg et al.[7] was a randomized controlled trial while the remaining were of retrospective observational design. The number of audio calls analyzed in each study ranged from 337 to 169,236 with the majority obtaining call audio from large, regional OHCA databases.

Among these dispatch-level studies, four utilized ML[7,26,28,29] and three employed both ML and DL[24,25,27]. ML and DL classification algorithms included attentive interpretable tabular learning (TabNet)[25], automatic speech recognition[27], binary logistic regression[24], convolutional neural network[24], lightGBM[25], Neural network[24], Random forest[24], XGBoost[25]. Four studies did not describe the specific classification algorithm used.[7,26,28,29]

Electrocardiogram waveform classification and prediction of outcomes

Twenty-four studies were identified that used AI for ECG waveform classification in OHCA and outcome prediction. The majority were published in the past five years and five from prior years. The majority were carried out through collaborations between multinational

Table 1 – Characteristics of studies aimed at prediction of return of spontaneous circulation outcomes and survival. ROSC = return of spontaneous circulation.

Prediction of ROSC and Survival (n = 15)	
Dates	**Frequency (%)**
2023	1 (7)
2022	5 (34)
2021	4 (27)
2020	2 (14)
2019	2 (14)
2009	1 (7)
Country of Study Origin	
Hong Kong	1 (7)
Japan	2 (14)
Korea	3 (20)
Singapore	1 (7)
Slovenia	1 (7)
Taiwan	1 (7)
United States	2 (14)
Multinational Collaboration	4 (27)
Patient Demographic	
Adults (<18 years)	10 (67)
Adults & Pediatrics	1 (7)
Not Specified	4 (27)
AI Branch	
Machine Learning	11
Machine Learning & Deep Learning	4
Classification Algorithm	
Artificial Neural Networks	1
Autoscore	2
Classification and Regression Tree	1
Decision Tree	4
Deep Neural Networks	2
Embedded Fully Convolutional Network	2
Gradient Boosting	2
K-Nearest Neighbor	5
Lagrangian Support Vector Machine	1
LightGBM	4
Logistic Regression	7
Multilayer Perceptron	3
Naïve Bayes	1
Neural Networks	1
Random Forest	15
Reduced Support Vector Machine	1
Regularized Logistic Regression	1
Support Vector Machine	6
Voting Classifier	1
XGBoost	4

groups in Europe and the United States utilizing ECG waveform data from multicenter databases. Among these studies, six (25%) aimed to predict defibrillation outcomes in ventricular fibrillation (VF)[30–35], five (21%) focused on rhythm classification[36–40], five (21%) developed algorithms to advise defibrillation versus no defibrillation[41–45], four (17%) focused specific on the classification of pulseless electrical activity (PEA) (i.e., PEA vs pseudo-PEA vs pulsed rhythm, or favorable-PEA vs non-favorable-PEA)[46–49], two (8%) aimed to predict survival outcomes[30,50] and two (8%) aimed to suppress CPR artifact to improve ECG segment analysis[36,37]. Additional studies aimed to develop ECG based classification algorithms to predict rearrest in the immediate post-ROSC period[51], predict the presence of a pulse during CPR[52], and predict myocardial infarction/acute coronary artery occlusion during CPR[53]

Among the studies of ECG segment analysis, fourteen used ML[30–32,35,36,38–40,47–52], nine used DL[33,34,37,38,41–46], and one used both ML and DL[38]. All studies utilized ECG waveform characteristics (i.e., VF amplitude/frequency, QRS size/amplitude) obtained from manual defibrillators, automated external defibrillators, and/or Holter monitors. Several studies additionally utilized thoracic impedance data[30,36,42,43,47–52] obtained from the manual defibrillator and end tidal carbon monoxide values[35,48,49]. Coult et al.[50] also added clinical variables including age (<60 or ≥60 years) and sex. The analyzed ECG segments ranged from 1-second to greater than 40-seconds and were primarily segments from continuous ECG waveform captured during OHCA resuscitation (10/24, 42%)[36,37,39–45,52]. Other studies analyzed more specific ECG segments including VF segments before and after defibrillator (9/24, 38%)[30–35,38,50,53], pulse-

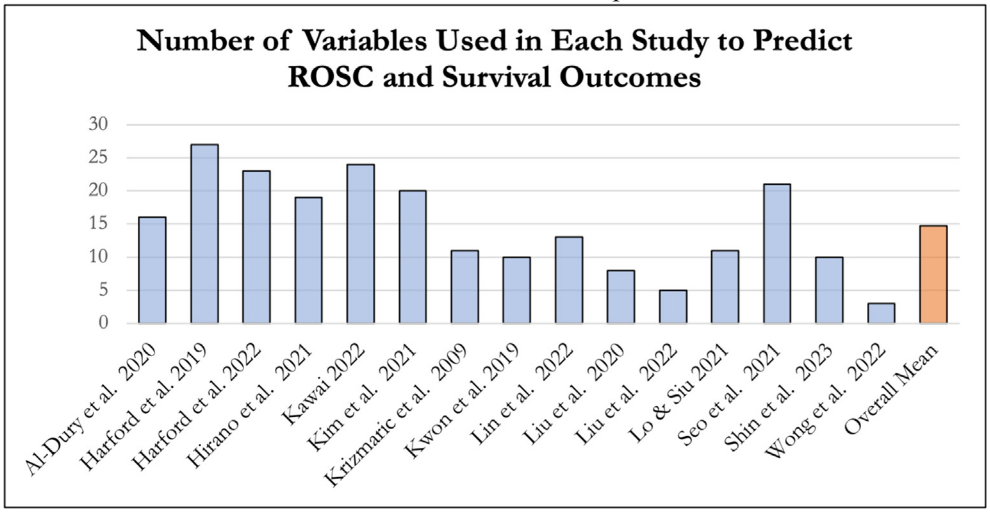

Fig. 4 – Number of inputted variables used in each study to predict return of spontaneous circulation and survival outcomes. ROSC = return of spontaneous circulation.

Table 2 – Characteristics of studies aimed at the early dispatch-level detection of out-of-hospital cardiac arrest and outcome prediction.

Early Dispatch-level Detection and Outcome Prediction for OHCA (n = 7)	
Year	**Frequency (%)**
2023	1 (15)
2022	2 (29)
2021	3 (43)
2019	1 (15)
Country of Study Origin	
Denmark	1 (15)
France	2 (29)
Sweden	1 (15)
Taiwan	1 (15)
Multinational Collaboration	2 (29)
Patient Demographic	
Adults & Pediatrics	7 (100)
AI Branch	
Machine Learning	4
Machine Learning & Deep Learning	3
Classification Algorithm	
Attentive Interpretable Tabular Learning	1
Automatic speech recognition	1
Binary logistic regression	1
Convolutional Neural Network	1
LightGBM	1
Neural network	1
Random forest	1
XGBoost	1
Not specified	4

less electrical activity (PEA) segments (4/24, 17%)[46–49], and immediate post-ROSC ECG segments (1/24, 4%)[51]

Other

Eight studies were identified that utilized AI to augment other aspects OHCA care. Three of these studies described their use of ML for spatial and temporal OHCA cluster detection and outcome prediction using clinical, demographic, or environmental factors.[54–56] Three retrospective studies employed ML to analyze OHCA patient care reports to evaluate data integrity and predict outcomes, one of which also used NLP.[57–59] Finally, two studies described the use of ML and DL to augment the lay rescuer and prehospital response to OHCA including chatbots to guide lay rescuer OHCA response[60] and the use of drones to deliver automated external defibrillators[61]

Table 3 – Studies included in this scoping review (n = 54).						
Category	**Title**	**Primary Author & Year**	**Country of Origin**	**Study Design**	**AI branch**	**Data Source**
Dispatch	Machine learning as a supportive tool to recognize cardiac arrest in emergency calls	Blomberg et al. 2019	Denmark, United States	Retrospective Observational	ML	Dispatch Audio
Dispatch	Effect of Machine Learning on Dispatcher Recognition of Out-of-Hospital Cardiac Arrest During Calls to Emergency Medical Services: A Randomized Clinical Trial	Blomberg et al. 2021	Denmark, United States	Randomized Clinical Trial	ML	Dispatch Audio
Dispatch	Machine learning can support dispatchers to better and faster recognize out-of-hospital cardiac arrest during emergency calls: A retrospective study	Byrsell et al. 2021	Sweden	Retrospective Observational	ML, DL	Dispatch Audio
Dispatch	Early recognition of a caller's emotion in out-ofhospital cardiac arrest dispatching: An artificial intelligence approach	Chin et al. 2021	Taiwan	Retrospective Observational	ML	Dispatch Audio
Dispatch	Privacy-Preserving Prediction of Victim's Mortality and Their Need for Transportation to Health Facilities	Arcolezi et al. 2022	France	Retrospective Observational	ML, DL	Dispatch Audio
Dispatch	Out-of-Hospital Cardiac Arrest Detection by Machine Learning Based on the Phonetic Characteristics of the Caller's Voice.	Rafi et al. 2022	France	Retrospective Observational	ML, DL	Dispatch Audio
Dispatch	When the machine is wrong. Characteristics of true and false predictions of Out-of-Hospital Cardiac Arrests in Emergency Calls using a machine-learning model	Blomberg et al. 2023	Denmark	Retrospective Observational	ML	Dispatch Audio
ECG	A method to predict ventricular fibrillation shock outcome during chest compressions	Coult et al. 2021	United States	Retrospective Observational	ML	ECG Waveform, Thoracic impedance
ECG	Ventricular Fibrillation Waveform Analysis During Chest Compressions to Predict Survival From Cardiac Arrest	Coult et al. 2019	United States	Retrospective Observational	ML	ECG Waveform, Thoracic impedance, Clinical Variables
ECG	Towards the Prediction of Rearrest during Out-of-Hospital Cardiac Arrest	Elola et al. 2020	Spain, United States	Retrospective Observational	ML	ECG Waveform
ECG	Multimodal Algorithms for the Classification of Circulation States During Out-of-Hospital Cardiac Arrest	Elola et al. 2020	Spain, Norway	Retrospective Observational	ML	ECG Waveform, Thoracic impedance, EtCO2
ECG	Capnography: A support tool for the detection of return of spontaneous circulation in out-of-hospital cardiac arrest	Elola et al. 2019	Spain, China, United States	Retrospective Observational	ML	ECG Waveform, Thoracic impedance
ECG	Deep Neural Networks for ECG-Based Pulse Detection during Out-of-Hospital Cardiac Arrest	Elola et al. 2019	Spain, United States	Retrospective Observational	DL	ECG Waveform, Thoracic impedance, EtCO2
ECG	Machine Learning Techniques for the Detection of Shockable Rhythms in Automated External Defibrillators	Figuera et al. 2016	Spain, Norway	Retrospective Observational	ML	ECG Waveform
ECG	Enhancing the accuracy of shock advisory algorithms in automated external defibrillators during ongoing cardiopulmonary resuscitation using a deep convolutional Encoder-Decoder filtering model	Hajeb et al. 2022	United States	Retrospective Observational	DL	ECG Waveform
ECG	Deep Neural Network Approach for Continuous ECG-Based Automated External Defibrillator Shock Advisory System During Cardiopulmonary Resuscitation.	Hajeb et al. 2021	United States	Retrospective Observational	DL	ECG Waveform
ECG	Combining Amplitude Spectrum Area with Previous Shock Information Using Neural Networks Improves Prediction Performance of Defibrillation Outcome for Subsequent Shocks in Out-Of-Hospital Cardiac Arrest Patients.	He et al. 2016	China	Retrospective Observational	DL	ECG Waveform

(*continued on next page*)

Table 3 (continued)

Category	Title	Primary Author & Year	Country of Origin	Study Design	AI branch	Data Source
ECG	Rhythm Analysis during Cardiopulmonary Resuscitation Using Convolutional Neural Networks.	Isasi et al. 2020	Spain, Norway	Retrospective Observational	DL	ECG Waveform, Thoracic impedance
ECG	Shock decision algorithm for use during load distributing band cardiopulmonary resuscitation	Isasi et al. 2021	Spain, Norway	Retrospective Observational	ML	ECG Waveform, Thoracic impedance
ECG	ECG derived feature combination versus single feature in predicting defibrillation success in out-of-hospital cardiac arrested patients	Ivanovic et al. 2019	Serbia, Germany, Italy	Retrospective Observational	ML	ECG Waveform
ECG	Predicting defibrillation success in out-of-hospital cardiac arrested patients: Moving beyond feature design	Ivanovic et al. 2020	Serbia, Germany, Italy	Retrospective Observational	ML	ECG Waveform
ECG	Shock Decision Algorithms for Automated External Defibrillators Based on Convolutional Networks	Jaureguibeitia et al. 2020	Spain	Retrospective Observational	DL	ECG Waveform, Thoracic impedance
ECG	Optimization of End-to-End Convolutional Neural Networks for Analysis of Out-of-Hospital Cardiac Arrest Rhythms during Cardiopulmonary Resuscitation.	Jekova & Krasteva 2021	Bulgaria	Retrospective Observational	DL	ECG Waveform
ECG	Fully Convolutional Deep Neural Networks with Optimized Hyperparameters for Detection of Shockable and Non-Shockable Rhythms.	Krasteva et al. 2020	Bulgaria, France	Retrospective Observational	DL	ECG Waveform
ECG	Prediction of countershock success using single features from multiple ventricular fibrillation frequency bands and feature combinations using neural networks	Neurauter et al. 2006	Austria, Norway, United States	Retrospective Observational	DL	ECG Waveform
ECG	Mixed convolutional and long short-term memory network for the detection of lethal ventricular arrhythmia.	Picon et al. 2019	Spain	Retrospective Observational	ML, DL	ECG Waveform
ECG	ECG-Based Classification of Resuscitation Cardiac Rhythms for Retrospective Data Analysis	Rad et al. 2017	Spain, Norway, United States	Retrospective Observational	ML	ECG Waveform
ECG	Machine learning and feature engineering for predicting pulse presence during chest compressions	Sashidhar et al. 2021	United States	Retrospective Observational	ML	ECG Waveform, Thoracic impedance
ECG	Integration of attributes from non-linear characterization of cardiovascular time-series for prediction of defibrillation outcomes	Shandilya et al. 2016	United States	Retrospective Observational	ML	ECG Waveform. EtCO2
ECG	Pilot study on VF-waveform based algorithms for early detection of acute myocardial infarction during out-of-hospital cardiac arrest	Thannhauser et al. 2022	Netherlands	Retrospective Observational	ML	ECG Waveform
ECG	A Machine Learning Model for the Prognosis of Pulseless Electrical Activity during Out-of-Hospital Cardiac Arrest.	Urteaga et al. 2021	Spain, United States	Retrospective Observational	ML	ECG Waveform, Thoracic impedance
Other	Machine Learning Analysis to Identify Data Entry Errors in Prehospital Patient Care Reports: A Case Study of a National Out-of-Hospital Cardiac Arrest Registry.	Choi et al. 2022	Korea	Retrospective Observational	ML, NLP	Clinical Variables
Other	Machine learning-based dispatch of drone-delivered defibrillators for out-of-hospital cardiac arrest.	Chu et al. 2020	Canada	Retrospective Observational	ML	Other
Other	Identification of Factors Associated with Return of Spontaneous Circulation after Pediatric Out-of-Hospital Cardiac Arrest Using Natural Language Processing	Harris et al. 2022	United States	Retrospective Observational	NLP	Clinical Variables
Other	Racial and Socioeconomic Disparities in Out-Of-Hospital Cardiac Arrest Outcomes: Artificial Intelligence-Augmented Propensity Score and Geospatial Cohort Analysis of 3,952 Patients.	Monlezun et al. 2021	United States	Retrospective Observational	ML	Demographic Variables
Other	Identification of out-of-hospital cardiac arrest clusters using unsupervised learning.	Moon et al.2022	Korea	Retrospective Observational	ML	Other

Table 3 (continued)

Category	Title	Primary Author & Year	Country of Origin	Study Design	AI branch	Data Source
Other	Machine learning model for predicting out-of-hospital cardiac arrests using meteorological and chronological data	Nakashima et al. 2020	United States, Japan	Retrospective Observational	ML	Other
Other	Association between type of bystander cardiopulmonary resuscitation and survival in out-of-hospital cardiac arrest: A machine learning study	Jerkeman et al. 2022	Sweden	Retrospective Observational	ML	Clinical Variables
Other	Can a voice assistant help bystanders save lives? A feasibility pilot study chatbot in beta version to assist OHCA bystanders.	Otero-Agra et al. 2022	Spain	Retrospective Observational	ML, DL	Other
ROSC Prediction	Prediction of ROSC After Cardiac Arrest Using Machine Learning	Liu et al. 2020	Singapore, Taiwan, Thailand, Korea, Japan, United Arab Emirates	Retrospective Observational	ML	Clinical Variables
ROSC Prediction	Development and validation of an interpretable prehospital return of spontaneous circulation (P-ROSC) score for patients with out-of-hospital cardiac arrest using machine learning: A retrospective study	Liu et al. 2022	Singapore, Korea, Taiwan, Japan	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Identifying the relative importance of predictors of survival in out of hospital cardiac arrest: a machine learning study	Al-Dury et al. 2020	Sweden, Norway	Retrospective Observational	ML	Clinical Variables
Survival Prediction	A machine learning approach for modeling decisions in the out of hospital cardiac arrest care workflow.	Harford et al.2022	United States	Retrospective Observational	ML, DL	Clinical Variables
Survival Prediction	A machine learning based model for Out of Hospital cardiac arrest outcome classification and sensitivity analysis.	Harford et al.2019	United States	Retrospective Observational	ML, DL	Clinical Variables
Survival Prediction	Early outcome prediction for out-of-hospital cardiac arrest with initial shockable rhythm using machine learning models.	Hirano et al. 2021	Japan	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Visual assessment of interactions among resuscitation activity factors in out-of-hospital cardiopulmonary arrest using amachine learning model	Kawai2022	Japan	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Developing a Time-Adaptive Prediction Model for Out-of-Hospital Cardiac Arrest: Nationwide Cohort Study in Korea.	Kim et al. 2021	Korea, United States	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Deep-learning-based out-of-hospital cardiac arrest prognostic system to predict clinical outcomes	Kwon et al.2019	Korea	Retrospective Observational	ML, DL	Clinical Variables
Survival Prediction	Tree-Based Algorithms and Association Rule Mining for Predicting Patients' Neurological Outcomes After First-Aid Treatment for an Out-of-Hospital Cardiac Arrest During COVID-19 Pandemic: Application of Data Mining	Lin et al. 2022	Taiwan	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Predicting Survived Events in Nontraumatic Out-of-Hospital Cardiac Arrest: A Comparison Study on Machine Learning and Regression Models	Lo & Siu2021	Hong Kong	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Prediction of Neurologically Intact Survival in Cardiac Arrest Patients without Pre-Hospital Return of Spontaneous Circulation: Machine Learning Approach	Seo et al. 2021	Korea	Retrospective Observational	ML	Clinical Variables
Survival Prediction	Development and validation of the SARICA score to predict survival after return of spontaneous circulation in out of hospital cardiac arrest using an interpretable machine learning framework.	Wong et al. 2022	Singapore	Retrospective Observational	ML	Clinical Variables
Survival Prediction/ ROSC	Intelligent analysis in predicting outcome of out-of-hospital cardiac arrest	Krizmaric et al. 2009	Slovenia	Retrospective Observational	ML	Clinical Variables
Survival Prediction/ ROSC	Evaluation of optimal scene time interval for out-of-hospital cardiac arrest using a deep neural network.	Shin et al. 2023	Korea	Retrospective Observational	ML, DL	Clinical Variables

Discussion

To date, there is a small but growing body of research evaluating the AI to support dispatchers, EMS clinicians, and physicians in OHCA care. The number of published studies detailing the feasibility and potential applications of AI have steadily increased since 2019. To our knowledge, we are the first to have evaluated the scope of literature on AI as decision-support in early OHCA resuscitation. We identified three main categories of studies that use AI to detect and predict outcomes in OHCA care: early dispatch-level detection of OHCA, prediction of ROSC and/or survival, and ECG waveform classification. In the prehospital setting where the dynamic nature requires rapid gathering and interpretation of limited information, harnessing the power of AI to quickly analyze data and predict outcomes may enhance our ability to deliver the most effective OHCA care.

The prediction of ROSC and survival early in the care continuum has the potential to guide resuscitation decisions for OHCA patients; yet accurate outcome prediction based on limited prehospital data represents a major challenge. In this scoping review, most of the studies evaluated the performance of different AI classification algorithms to predict the binary outcome(s) of survival and/or neurologically intact survival. The majority of studies compared the predictive performance of multiple different ML or DL classification algorithms. Two different studies by Liu et al. additionally compared a single ML classification algorithm to previously validated predictive models based on standard logistic regression including the ROSC After Cardiac Arrest score (RACA) and Utstein reporting-based ROSC score (UB-ROSC).[12,15] Kim et al. developed a time-adaptive ML algorithm to predict percent survival and neurologically intact survival minute-by-minute for OHCA patients up to 60 minutes.[14]

When assessing factors in each study predicting ROSC and survival, there was significant heterogeneity. While some studies included as few as three predictors, others included as many as 27. Other studies utilized data available at the time of ambulance arrival while further studies included data up to the time of care transfer to ED staff. Al-Dury et al.[13] evaluated the relative importance of factors for predicting survival present at the time of ambulance arrival and found that initial rhythm (most important), age, time to CPR initiation, EMS response time, and location of cardiac arrest were the top five most important. Lin et al.[11] assessed the relative importance of factors available during the entire out-of-hospital course and upon ED arrival and found that prehospital ROSC, age, EMS response time, scene time, and transport time were the five most important factors, with prehospital ROSC being the most important. Overall, the use of AI to prognosticate outcomes at different time points may benefit different care teams including EMS providers (i.e., informing transport or field termination of resuscitation) and ED physicians (i.e., informing the length of additional resuscitation or care discussions with families).

Despite the growing number of studies evaluating AI to predict ROSC and survival outcomes in OHCA, the generalizability of the predictive models developed to date may be limited. Most of these studies utilized classification algorithms that were developed and validated with data from EMS systems in Asia.[9–11,13–19,21] It is known that EMS systems vary widely both at the international level and within the United States.[62] As such, these models may not be applicable within the North American and European EMS systems.

Improving timely recognition of OHCA during the initial medical dispatch call is another factor that may improve OHCA outcomes. Early detection of OHCA is critical as it may enable telephone CPR and dispatch of appropriate EMS resources. This scoping review identified multiple studies which described ML and DL frameworks which analyze linguistic and phonetic characteristics of speech during the dispatch call and provided decision-support for dispatch in the detection of OHCA. Blomberg et al.[7] conducted the first randomized controlled trial evaluating the use of ML as real-time decision support for OHCA recognition for dispatchers. Though the model had previously shown success in training and validation during a prior retrospective observational study[29], it did not result in a significant improvement in dispatcher OHCA recognition when used in real-time. The absence of a significant improvement was attributed to human factors in the interaction with the decision support tool. This study highlighted the first prospective implementation of ML to guide early OHCA care. Overall, this scoping review revealed that current literature consists of retrospective analyses with positive conclusions and a single randomized control trial with a neutral outcome. As such, these findings demonstrate the need for future prospective studies to better elucidate the factors impacting the use of AI in real-time to support dispatch and prehospital care.

This scoping review further identified studies which used AI to analyze ECG waveform segments from OHCA resuscitations. These studies were heterogenous in both their objectives and approaches; nonetheless the overarching aims were to limit CPR interruptions through rapid analysis of ECG segments (both with and without CPR artifact) with a variety of classification algorithms. While some studies used ML algorithms to classify ECG segments obtained during CPR pauses[46–49], other studies allowed classified rhythms with on-going CPR through removal of artifact via filtering.[30,36,38,42,50,52] Other studies utilized feature extraction and rhythm classification via DL from ECG segments taken during CPR which eliminated the need for CPR artifact filtering.[37,41,44,45,53] Additional studies attempted to characterize specific features of VF in order to predict defibrillation performance[30–35,43] while others targeted overall rhythm classification[39,40] Finally, Coult et al.[50] conducted a study using ECG waveform and thoracic impedance data obtained from the defibrillator and combined it with clinical variables in an attempt to predict survival outcomes.

Limitations

The results of this scoping review must be considered within the context of multiple limitations. This review may not encompass literature published by nursing and allied health professionals given that databases such as the Cumulated Index to Nursing and Allied Health Literature were not included. Similarly, more technical engineering studies in databases such as Institute of Electrical and Electronics Engineers may not have been included. Further, findings may lack external validity due to the limited number of countries from which studies were published. Conference abstracts, which lack complete methodology and outcome descriptions, were also excluded and this may have limited the breadth of emerging research. Finally, a single experienced reviewer screened manuscripts which may have led to bias toward over- or under-inclusion of articles; however, a previous study showed that it is unlikely to have significantly changed the overall results.[63]

Conclusions

A growing body of literature exists describing the use of AI to support providers in the early care of OHCA. The main categories that were identified included studies that aimed to improve the early dispatch-level detection of OHCA, predict ROSC and survival outcomes, and classify of ECG rhythms. Only one prospective trial was identified, and future trials are needed to evaluate the integration of AI with human decision-making and gestalt. Nonetheless, these 54 studies demonstrate the potential applicability of AI algorithms to support dispatchers, EMS providers and physicians, and ED-based physicians in the OHCA care.

CRediT authorship contribution statement

Jake Toy: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Nichole Bosson:** Supervision, Writing – review & editing. **Shira Schlesinger:** Supervision, Writing – review & editing. **Marianne Gausche-Hill:** Supervision, Writing – review & editing. **Samuel Stratton:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Jake Toy, DO, Declarations of interest: none. Nichole Bosson, MD, MPH, Declarations of interest: none. Shira Schlesinger, MD, MPH, Declarations of interest: none, Marianne Gausche-Hill, MD, Declarations of interest: Member of the CARES Advisory Board beginning in September 2023. Sam Stratton, MD, Declarations of interest: none].

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resplu.2023.100491.

Author details

[a]University of California Los Angeles, Fielding School of Public Health, 650 Charles E Young Drive South, Los Angeles, CA 90095, USA [b]Harbor-UCLA Department of Emergency Medicine & The Lundquist Research Institute, 1000 W Carson Street, Torrance, CA 90502, USA[c]Los Angeles County EMS Agency, 10100 Pioneer Blvd, Santa Fe Springs, CA 90670, USA [d]Orange County California Emergency Medical Services Agency, 405 W. 5th Street, Santa Ana, CA 92705, USA [e]David Geffen School of Medicine at UCLA, Department of Emergency Medicine, 10833 Le Conte Ave, Los Angeles, CA 90095, USA

REFERENCES

1. 2021 CARES Annual Report. Accessed December 9, 2022. https://mycares.net/sitepages/uploads/2022/2021_flipbook/index.html?page=1.
2. Part 12: From Science to Survival | Circulation. Accessed October 28, 202. https://www.ahajournals.org/doi/10.1161/circ.102.suppl_1.I-358.
3. Kirubarajan A, Taher A, Khan S, Masood S. Artificial intelligence in emergency medicine: A scoping review. J Am Coll Emerg Physicians Open 2020;1:1691–702. https://doi.org/10.1002/emp2.12277.
4. Alamgir A, Mousa O, Shah Z. Artificial intelligence in predicting cardiac arrest: scoping review. JMIR Med Inform 2021;9:e30798.
5. Viderman D, Abdildin YG, Batkuldinova K, Badenes R, Bilotta F. Artificial Intelligence in Resuscitation: A Scoping Review. J Clin Med 2023;12:2254. https://doi.org/10.3390/jcm12062254.
6. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation | Annals of Internal Medicine. Accessed April 3, 2023. https://www.acpjournals.org/doi/10.7326/M18-0850.
7. Blomberg SN, Christensen HC, Lippert F, et al. Effect of machine learning on dispatcher recognition of out-of-hospital cardiac arrest during calls to emergency medical services: A randomized clinical trial. JAMA Netw Open 2021;4:e2032320.
8. Harford S, Del Rios M, Heinert S, et al. A machine learning approach for modeling decisions in the out of hospital cardiac arrest care workflow. BMC Med Inf Decis Making 2022;22:21. https://doi.org/10.1186/s12911-021-01730-4.
9. Kawai Y, Okuda H, Kinoshita A, et al. Visual assessment of interactions among resuscitation activity factors in out-of-hospital cardiopulmonary arrest using a machine learning model. PLoS One 2022;17:e0273787.
10. Wong XY, Ang YK, Li K, et al. Development and validation of the SARICA score to predict survival after return of spontaneous circulation in out of hospital cardiac arrest using an interpretable machine learning framework. Resuscitation 2022;170:126–33. https://doi.org/10.1016/j.resuscitation.2021.11.029.
11. Lin WC, Huang CH, Chien LT, et al. Tree-based algorithms and association rule mining for predicting patients' neurological outcomes after first-aid treatment for an out-of-hospital cardiac Arrest During COVID-19 pandemic: application of data mining. Int J Gen Med 2022;15:7395–405. https://doi.org/10.2147/IJGM.S384959.
12. Liu N, Liu M, Chen X, et al. Development and validation of an interpretable prehospital return of spontaneous circulation (P-ROSC) score for patients with out-of-hospital cardiac arrest using machine learning: A retrospective study. eClinicalMedicine101422 2022;48. https://doi.org/10.1016/j.eclinm.2022.101422.
13. Al-Dury N, Ravn-Fischer A, Hollenberg J, et al. Identifying the relative importance of predictors of survival in out of hospital cardiac arrest: a machine learning study. Scand J Trauma Resusc Emerg Med 2020;28:60. https://doi.org/10.1186/s13049-020-00742-9.
14. Kim JW, Ha J, Kim T, et al. Developing a time-adaptive prediction model for out-of-hospital cardiac arrest: nationwide cohort Study in Korea. J Med Internet Res 2021;23:e28361.
15. Liu N, Ho AFW, Pek PP, et al. Prediction of ROSC After Cardiac Arrest Using Machine Learning. *Stud Health Technol Inform.* 2020;270((Liu N.) Health Services Research Centre, Singapore Health Services, Singapore):1357–1358. https://doi.org/10.3233/SHTI200440.
16. Shin SJ, Bae HS, Moon HJ, et al. Evaluation of optimal scene time interval for out-of-hospital cardiac arrest using a deep neural network. Am J Emerg Med 2023;63:29–37. https://doi.org/10.1016/j.ajem.2022.10.011.
17. Seo DW, Yi H, Bae HJ, et al. Prediction of neurologically intact survival in cardiac arrest patients without pre-hospital return of spontaneous circulation: machine learning approach. J Clin Med 2021;10. https://doi.org/10.3390/jcm10051089.
18. Kwon JM, Jeon KH, Kim HM, et al. Deep-learning-based out-of-hospital cardiac arrest prognostic system to predict clinical outcomes. Resuscitation 2019;139:84–91. https://doi.org/10.1016/j.resuscitation.2019.04.007.
19. Hirano Y, Kondo Y, Sueyoshi K, Okamoto K, Tanaka H. Early outcome prediction for out-of-hospital cardiac arrest with initial shockable rhythm using machine learning models. Resuscitation 2021;158:49–56. https://doi.org/10.1016/j.resuscitation.2020.11.020.

20. Harford S, Darabi H, Del Rios M, et al. A machine learning based model for Out of Hospital cardiac arrest outcome classification and sensitivity analysis. Resuscitation 2019;138:134–40. https://doi.org/10.1016/j.resuscitation.2019.03.012.
21. Lo YH, Siu YCA. Predicting survived events in nontraumatic out-of-hospital cardiac arrest: A comparison study on machine learning and regression models. J Emerg Med 2021;61:683–94. https://doi.org/10.1016/j.jemermed.2021.07.058.
22. Krizmaric M, Verlic M, Stiglic G, Grmec S, Kokol P. Intelligent analysis in predicting outcome of out-of-hospital cardiac arrest. Comput Methods Programs Biomed 2009;95:S22–32. https://doi.org/10.1016/j.cmpb.2009.02.013.
23. Liu N, Ho AFW, Pek PP, et al. Prediction of ROSC after cardiac arrest using machine learning. Stud Health Technol Inform 2020;270:1357–8. https://doi.org/10.3233/SHTI200440.
24. Rafi S, Gangloff C, Paulhet E, et al. Out-of-hospital cardiac arrest detection by machine learning based on the phonetic characteristics of the caller's voice. Stud Health Technol Inform 2022;294:445–9. https://doi.org/10.3233/SHTI220498.
25. Arcolezi HH, Cerna S, Couchot JF, Guyeux C, Makhoul A. Privacy-preserving prediction of victim's mortality and their need for transportation to health facilities. IEEE Trans Ind Inform 2022;18:5592–9. https://doi.org/10.1109/TII.2021.3123588.
26. Blomberg SN, Jensen TW, Porsborg Andersen M, et al. When the machine is wrong. Characteristics of true and false predictions of Out-of-Hospital Cardiac Arrests in Emergency Calls using a machine-learning model. *Resuscitation*. Published online January 9, 2023:109689. https://doi.org/10.1016/j.resuscitation.2023.109689.
27. Byrsell F, Claesson A, Ringh M, et al. Machine learning can support dispatchers to better and faster recognize out-of-hospital cardiac arrest during emergency calls: A retrospective study. Resuscitation 2021;162:218–26. https://doi.org/10.1016/j.resuscitation.2021.02.041.
28. Chin KC, Hsieh TC, Chiang WC, et al. Early recognition of a caller's emotion in out-of-hospital cardiac arrest dispatching: An artificial intelligence approach. Resuscitation 2021;167:144–50. https://doi.org/10.1016/j.resuscitation.2021.08.032.
29. Blomberg SN, Folke F, Ersbøll AK, et al. Machine learning as a supportive tool to recognize cardiac arrest in emergency calls. Resuscitation 2019;138:322–9. https://doi.org/10.1016/j.resuscitation.2019.01.015.
30. Coult J, Rea TD, Blackwood J, Kudenchuk PJ, Liu C, Kwok H. A method to predict ventricular fibrillation shock outcome during chest compressions. Comput Biol Med 2021;129:104136. https://doi.org/10.1016/j.compbiomed.2020.104136.
31. Ivanović MD, Hannink J, Ring M, et al. Predicting defibrillation success in out-of-hospital cardiac arrested patients: Moving beyond feature design. Artif Intell Med 2020;110:101963. https://doi.org/10.1016/j.artmed.2020.101963.
32. Ivanović MD, Ring M, Baronio F, et al. ECG derived feature combination versus single feature in predicting defibrillation success in out-of-hospital cardiac arrested patients. Biomed Phys Eng Express 2019;5. https://doi.org/10.1088/2057-1976/aaebec.
33. He M, Lu Y, Zhang L, Zhang H, Gong Y, Li Y. Combining amplitude spectrum area with previous shock information using neural networks improves prediction performance of defibrillation outcome for subsequent shocks in out-of-hospital cardiac arrest patients. PLoS One 2016;11:e0149115.
34. Neurauter A, Eftestøl T, Kramer-Johansen J, et al. Prediction of countershock success using single features from multiple ventricular fibrillation frequency bands and feature combinations using neural networks. Resuscitation 2007;73:253–63. https://doi.org/10.1016/j.resuscitation.2006.10.002.
35. Shandilya S, Kurz MC, Ward KR, Najarian K. Integration of attributes from non-linear characterization of cardiovascular time-series for prediction of defibrillation outcomes. PLoS One 2016;11. https://doi.org/10.1371/journal.pone.0141313.
36. Isasi I, Irusta U, Aramendi E, Olsen JA, Wik L. Shock decision algorithm for use during load distributing band cardiopulmonary resuscitation. Resuscitation 2021;165:93–100. https://doi.org/10.1016/j.resuscitation.2021.05.028.
37. Hajeb-M S, Cascella A, Valentine M, Chon KH. Enhancing the accuracy of shock advisory algorithms in automated external defibrillators during ongoing cardiopulmonary resuscitation using a deep convolutional Encoder-Decoder filtering model. Expert Syst Appl 2022;203. https://doi.org/10.1016/j.eswa.2022.117499.
38. Picon A, Irusta U, Álvarez-Gila A, et al. Mixed convolutional and long short-term memory network for the detection of lethal ventricular arrhythmia. PLoS One 2019;14:e0216756.
39. Rad AB, Eftestol T, Engan K, et al. ECG-based classification of resuscitation cardiac rhythms for retrospective data analysis. IEEE Trans Biomed Eng 2017;64:2411–8. https://doi.org/10.1109/TBME.2017.2688380.
40. Figuera C, Irusta U, Morgado E, et al. Machine learning techniques for the detection of Shockable rhythms in automated external defibrillators. PLoS One 2016;11:e0159654.
41. Jekova I, Krasteva V. Optimization of end-to-end convolutional neural networks for analysis of out-of-hospital cardiac arrest rhythms during cardiopulmonary resuscitation. Sensors 2021;21. https://doi.org/10.3390/s21124105.
42. Isasi I, Irusta U, Aramendi E, Eftestøl T, Kramer-Johansen J, Wik L. Rhythm analysis during cardiopulmonary resuscitation using convolutional neural networks. Entropy Basel Switz 2020;22. https://doi.org/10.3390/e22060595.
43. Jaureguibeitia X, Zubia G, Irusta U, et al. Shock decision algorithms for automated external defibrillators based on convolutional networks. IEEE Access 2020;8:154746–58. https://doi.org/10.1109/ACCESS.2020.3018704.
44. Krasteva V, Ménétré S, Didon JP, Jekova I. Fully convolutional deep neural networks with optimized hyperparameters for detection of shockable and non-Shockable rhythms. Sensors 2020;20. https://doi.org/10.3390/s20102875.
45. Hajeb-M S, Cascella A, Valentine M, Chon KH. Deep neural network approach for continuous ECG-Based automated external defibrillator shock advisory system during cardiopulmonary resuscitation. J Am Heart Assoc 2021;10:e019065.
46. Elola A, Aramendi E, Irusta U, et al. Deep neural networks for ECG-based pulse detection during out-of-hospital cardiac arrest. Entropy Basel Switz 2019;21. https://doi.org/10.3390/e21030305.
47. Urteaga J, Aramendi E, Elola A, Irusta U, Idris A. A machine learning model for the prognosis of pulseless electrical activity during out-of-hospital cardiac arrest. Entropy Basel Switz 2021;23. https://doi.org/10.3390/e23070847.
48. Elola A, Aramendi E, Irusta U, Berve PO, Wik L. Multimodal algorithms for the classification of circulation states during out-of-hospital cardiac arrest. IEEE Trans Biomed Eng 2021;68:1913–22. https://doi.org/10.1109/TBME.2020.3030216.
49. Elola A, Aramendi E, Irusta U, et al. Capnography: A support tool for the detection of return of spontaneous circulation in out-of-hospital cardiac arrest. Resuscitation 2019;142:153–61. https://doi.org/10.1016/j.resuscitation.2019.03.048.
50. Coult J, Blackwood J, Sherman L, Rea TD, Kudenchuk PJ, Kwok H. Ventricular fibrillation waveform analysis during chest compressions to predict survival from cardiac arrest. Circ Arrhythm Electrophysiol 2019;12:e006924.
51. Elola A, Aramendi E, Rueda E, Irusta U, Wang H, Idris A. Towards the prediction of rearrest during out-of-hospital cardiac arrest. Entropy Basel Switz 2020;22. https://doi.org/10.3390/e22070758.
52. Sashidhar D, Kwok H, Coult J, et al. Machine learning and feature engineering for predicting pulse presence during chest compressions. R Soc Open Sci 2021;8:210566. https://doi.org/10.1098/rsos.210566.
53. Thannhauser J, Nas J, van der Sluijs K, et al. Pilot study on VF-waveform based algorithms for early detection of acute myocardial infarction during out-of-hospital cardiac arrest. *Resuscitation*.

2022;174((Thannhauser J., Jos.Thannhauser@Radboudumc.nl; Nas J.; van der Sluijs K.; de Boer M.-J.; van Royen N.; Bonnes J.; Brouwer M.) Department of Cardiology, Radboudumc, Nijmegen, Netherlands):62–67. https://doi.org/10.1016/j.resuscitation.2022.03.025.

54. Monlezun DJ, Samura AT, Patel RS, Thannoun TE, Balan P. Racial and socioeconomic disparities in out-of-hospital cardiac arrest outcomes: artificial intelligence-augmented propensity score and geospatial cohort analysis of 3,952 Patients. Cardiol Res Pract 2021;2021:3180987. https://doi.org/10.1155/2021/3180987.
55. Moon HJ, Shin YJ, Cho YS. Identification of out-of-hospital cardiac arrest clusters using unsupervised learning. Am J Emerg Med 2022;62:41–8. https://doi.org/10.1016/j.ajem.2022.09.035.
56. Nakashima T, Ogata S, Noguchi T, et al. Machine learning model for predicting out-of-hospital cardiac arrests using meteorological and chronological data. Heart Br Card Soc 2021;107:1084–91. https://doi.org/10.1136/heartjnl-2020-318726.
57. Harris M, Crowe RP, Anders J, D'Acunto S, Adelgais KM, Fishe JN. Identification of Factors Associated with Return of Spontaneous Circulation after Pediatric Out-of-Hospital Cardiac Arrest Using Natural Language Processing. *Prehosp Emerg Care.* Published online May 23, 2022:1-8. https://doi.org/10.1080/10903127.2022.2074180.
58. Choi DH, Park JH, Choi YH, Song KJ, Kim S, Shin SD. Machine Learning Analysis to Identify Data Entry Errors in Prehospital Patient Care Reports: A Case Study of a National Out-of-Hospital Cardiac Arrest Registry. *Prehosp Emerg Care*. Published online November 16, 2022:1–9. https://doi.org/10.1080/10903127.2022.2137745.
59. Jerkeman M, Lundgren P, Omerovic E, et al. Association between type of bystander cardiopulmonary resuscitation and survival in out-of-hospital cardiac arrest: A machine learning study. Resusc Plus 2022;10:100245. https://doi.org/10.1016/j.resplu.2022.100245.
60. Otero-Agra M, Jorge-Soto C, Cosido-Cobos ÓJ, et al. Can a voice assistant help bystanders save lives? A feasibility pilot study chatbot in beta version to assist OHCA bystanders. Am J Emerg Med 2022;61:169–74. https://doi.org/10.1016/j.ajem.2022.09.013.
61. Chu J, Leung KHB, Snobelen P, et al. Machine learning-based dispatch of drone-delivered defibrillators for out-of-hospital cardiac arrest. Resuscitation 2021;162:120–7. https://doi.org/10.1016/j.resuscitation.2021.02.028.
62. Spigner MF, Benoit JL, Menegazzi JJ, McMullan JT. Prehospital protocols for post-return of spontaneous circulation are highly variable. Prehosp Emerg Care 2021;25:191–5. https://doi.org/10.1080/10903127.2020.1754979.
63. Waffenschmidt S, Knelangen M, Sieben W, Bühn S, Pieper D. Single screening versus conventional double screening for study selection in systematic reviews: a methodological systematic review. BMC Med Res Method 2019;19:132. https://doi.org/10.1186/s12874-019-0782-0.