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Challenges and Opportunities of Artificial Intelligence Implementation in the Management of Out-of-Hospital Cardiac Arrest: Scoping Review

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SCOPING REVIEW

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ABSTRACT

Out-of-hospital cardiac arrest (OHCA) remains a major global health challenge with low survival rates. Artificial intelligence (AI) has emerged as a promising tool to enhance early detection, response, and management of OHCA cases. This study explores the current use of AI in OHCA, identifying challenges and opportunities related to its implementation. This scoping review followed the PRISMA-ScR guidelines, utilizing a systematic search of international databases to identify relevant literature. A total of 10 studies were included, comprising cohort studies, observational studies, randomized controlled trials (RCTs), and pilot projects from 10 different countries. AI implementation in OHCA management demonstrated several opportunities, including improved early detection (increasing sensitivity by 5.5–15% and reducing EMS response time by up to 26 seconds), enhanced decision support for termination of resuscitation (with specificity up to 99.0%), and increased bystander engagement through real-time CPR guidance. However, challenges remain, such as data privacy, ethical concerns (especially with visual surveillance and GDPR compliance), infrastructure limitations, and variability in local protocol. The paradox between faster detection and improved CPR quality was also noted. AI has significant potential to improve OHCA outcomes by optimizing detection, response, and clinical decision-making. Successful implementation requires multidisciplinary collaboration, robust external validation, and ethical considerations to address privacy and local adaptation. Integrating AI into emergency systems and public training can enhance survival rates, but further large-scale studies are needed to ensure effectiveness and equity.

Key Messages:

- AI can improve early detection, response time, and clinical decision-making in OHCA, with promising impacts on survival outcomes. In contrast, a novel gap in its use for non-medical bystander training was identified. It also emphasizes the need for ethical frameworks, data governance, and local model validation to ensure equitable and sustainable implementation.

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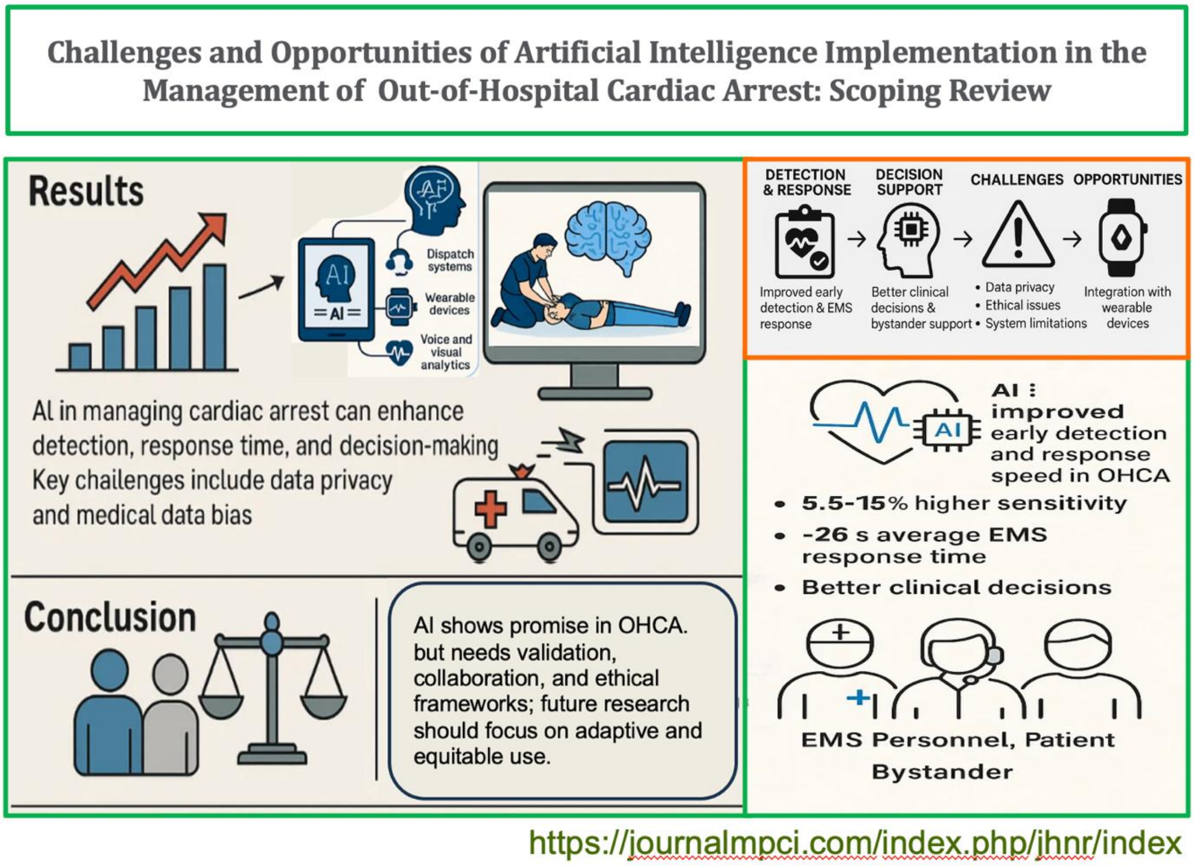
GRAPHICAL ABSTRACT



INTRODUCTION

Out-of-hospital cardiac arrest (OHCA), characterized by the sudden cessation of cardiac activity outside clinical settings (1), is a major global health challenge with an estimated annual incidence of 50-60 cases per 100,000 population worldwide (2). In industrialized countries, out-of-hospital cardiac arrest leads to more than 700,000 deaths each year in Europe and the United States alone (3), including 436,000 cases recorded in one year in the U.S. (4). Data from various countries confirms that OHCA is a relatively common occurrence and can happen to anyone at any time (5). Despite decades of research and advances in resuscitation techniques, survival rates remain alarmingly low at 5-10% (6), with most individuals dying before reaching the hospital or shortly thereafter (1). The persistently high incidence and low survival rates underscore the urgent need for innovative solutions to improve patient outcomes. While increasing public awareness, expanding CPR training, and optimizing emergency response systems are important measures and align with the American Heart Association's goals (7), ongoing challenges in reducing mortality highlight the critical importance of addressing this problem.

The development of artificial intelligence (AI) technology offers new opportunities in the management of OHCA. Using algorithms and data learning models (8–10), AI has improved early detection, decision-making, and rapid response to OHCA cases (11). Studies have shown that AI can analyse data from patient devices to detect early signs of cardiac arrest, provide real-time data-driven resuscitation recommendations, and even provide CPR guidance to laypeople through AI-based applications (11). In addition, innovations such as voice analysis of emergency calls, use of sensors in wearable devices, and integration of AI in portable AEDs have improved the speed and accuracy of diagnosis and the effectiveness of early intervention. (12–15)

However, several obstacles and knowledge gaps still need to be addressed. Lack of Studies on the real-world implementation of AI, particularly in training and supporting lay helpers, is limited (16,17). Other challenges include infrastructure limitations, user training needs, and complex ethical and data

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privacy issues, especially in wearable technology and online health data integration (18–20). In addition, algorithm bias that may affect detection accuracy in certain demographic groups, such as women and the elderly, is also a concern (18). These gaps indicate the need for further research to evaluate the effectiveness, challenges, and opportunities of comprehensive AI implementation in OHCA management.

Therefore, this study aims to explore using artificial intelligence applications in out-of-hospital cardiac arrest management, identify challenges and opportunities for implementation, and map the existing literature regarding its impact on patient survival rates and clinical outcomes. This study also hypothesises that integrating multimodal AI systems, combining wearable sensors, computer vision, and voice analysis, will improve early detection accuracy, speed up emergency response, and reduce demographic bias in OHCA management compared to conventional methods. Thus, the results of this study are expected to provide relevant recommendations for the development of AI-based interventions in the future, in order to improve the effectiveness of OHCA management and reduce the mortality rate that is still high today.

METHODS

The design used in this study is a scoping review. A scoping review is a flexible methodological approach to explore emerging and rapidly developing topics(21). The PRISMA Extension for Scoping Reviews (PRISMA-ScR) is utilized in this literature review to identify the challenges and opportunities associated with implementing Artificial Intelligence (AI) in out-of-hospital cardiac arrest. This design offers a more comprehensive conceptual scope, enabling the explanation of various relevant research outcomes. The framework for this scoping review consists of five core stages: identifying the review question, identifying relevant research findings, selecting studies, mapping the data, and compiling, summarizing, and reporting the results (21).

Search Strategy

The identification of articles was conducted systematically. Two authors, H.D. and A.N., independently performed a structured literature search using six central databases: PubMed, ScienceDirect, Scopus, EBSCOhost, and the search engines Google and Google Scholar. Boolean operators "AND" and "OR" were applied to refine or broaden the search results across various tenses, utilizing the following keywords and MeSH terms (Table 1). To ensure comprehensive coverage, grey literature was also searched using Google to identify relevant Pilot project reports and unpublished materials closely related to the review topic.

Eligibility Criteria

The process of selecting articles for this review was conducted by the authors following the PRISMA Extension for Scoping Reviews (PRISMA-ScR) guidelines (see Figure 1). The research question and the eligibility criteria for the reviewed articles were determined using the PCC approach (Population, Concept, and Context).

P (Population) : Individuals who experienced Out-of-Hospital Cardiac Arrest.
C (Concept) : Implementation of Artificial Intelligence in handling OHCA
C (Context) : Pre-hospital setting

This review excluded inaccessible full-text articles not written in English or classified as secondary research. The inclusion criteria were full-text articles that were accessible, published in English, and categorized as primary studies (original articles) and Pilot projects. Furthermore, the review applied a publication year restriction of the last 10 years, which is in line with the rapid development of AI in recent years.

Data Collection and Analysis

Study Selection and Quality Appraisal

The authors independently selected studies that met the eligibility criteria, starting by checking for duplicates using Mendeley. Then, the authors evaluated the relevance of the studies based on the title, abstract, and full text according to the inclusion and exclusion criteria. Each study was assessed using the Joanna Briggs Institute 2022 critical appraisal checklist, scoring 1 for "Yes" and 0 for all other answers. All included articles met the eligibility criteria, and studies with a JBI score below 70% were excluded. In this

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review, a grey literature (pilot project) was also included and assessed for eligibility using the AACODS checklist. There were no disagreements between the authors and supervisors regarding the eligibility of the selected studies.

Data Extraction and Analysis

In this review, each article included in the search was summarized in a table that provides a detailed overview of all results related to the topic discussed. The information presented in the extraction table relates to the study characteristics: author, design, country, objective, intervention, and the study's results. Research findings on the challenges and opportunities of using artificial intelligence in Out-of-Hospital Cardiac Arrest cases were also identified. All studies included are primary research studies and pilot projects. Therefore, data analysis was carried out thematically using a descriptive exploratory approach. The data analysis process began with identifying and presenting the data as a table based on the reviewed articles. After obtaining the data, the authors analyzed and explained each finding based on the review results. Finally, the authors double-checked the included studies to ensure accuracy and minimize errors

Table 1. Keywords and MeSH terms

PCC	Keyword	MeSH terms
P (Population)	Out-of-hospital cardiac arrest, OHCA patients, bystanders	Cardiac arrest, Out of Hospital Aardiac Arrest " OR "OHCA"
C (Concept)	Artificial Intelligence, AI implementation, barriers, opportunities	Artificial intelligence" OR "machine learning" OR "AI" challenges" OR "opportunities"
C (Context)	Emergency care, pre-hospital response, public health	Emergency medical services"OR "dispatcher" OR "prehospital care"

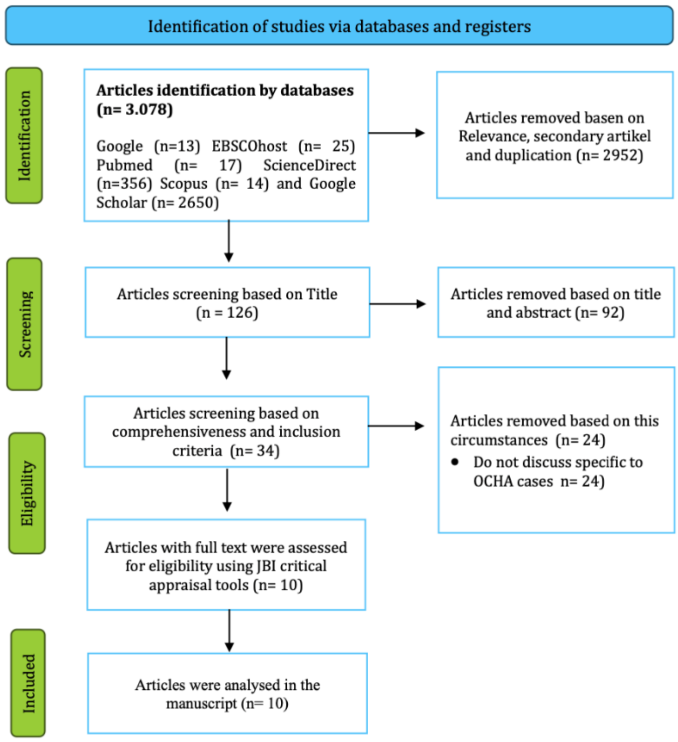

Figure 1. PRISMA Flow Diagram adapted from Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372:n71. Creative Commons

RESULTS

Study Selection Results

The initial identification from five databases using the predefined keywords resulted in 3.078 articles. A check for duplicates and screening based on titles and abstracts was then conducted, leaving 126 articles. During the title and abstract screening stage, the authors excluded 92 articles, leaving 34 to be screened based on the inclusion criteria. 9 articles and 1 pilot project were analyzed in this review, all of

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which passed the eligibility stage (See Figure 1).

Characteristics of the Included Studies

In this review, most of the studies analyzed had an experimental design, including four Retrospective Cohort study, Two retrospective observationa studies, Two cross-sectional study and one each of a RCT,and Pilot project report (see Table 2). The studies included were conducted in various countries, such as the United States of America (n=2), Denmark (n=2), France, Japan, Taiwan, the United Kingdom, and Lithuania. The population characteristics in AI studies for OHCA generally include adult patients who experienced cardiac arrest outside the hospital, with data sourced from national registries or EMS systems in developed countries. In addition to patients, the population includes EMS personnel, emergency dispatch operators, and community members as bystanders or educational targets. Some studies focus on urban areas with advanced emergency response systems, while others cover broader populations using audio data, CCTV, or public simulations.

Study Outcome

The study identified and categorised potential and interesting challenges and findings on implementing AI in out-of-hospital cardiac arrest cases (see Table 3). Implementing artificial intelligence (AI) in out-of-hospital cardiac arrest (OHCA) management shows transformative potential and significant improvements in detection accuracy and response speed. AI in the OHCA study improved early detection (5.5-15% higher sensitivity), reduced average EMS response time by 26 seconds, potentially increasing survival rates by 33 cases if bystander CPR interventions were optimised, and supported better clinical decisions, potentially saving more lives and reducing resuscitation errors by 54 cases (22,29). EENA & Corti's (2020) pilot projects in France and Italy showed that AI integration in dispatch systems improved OHCA detection by 5.5% and 3.9% in both countries, with identification times 2 minutes faster than humans, despite local protocol variations and limited historical data(31). Kajino et al. (2024) developed an AI-based Termination of Resuscitation (TOR) model that achieved an AUC of 0.952, outperforming the universal TOR rule in specificity (99.0% vs. 95.9%) (22). Voice analysis by Rafi et al. (2022) identified phonetic parameters such as fundamental frequency and intensity as markers of bystander stress, with the machine learning model achieving 84.1% sensitivity in detecting OHCA (28).

Interesting findings lie in the ability of AI to process complex conversations in real-time, as Corti demonstrated in reducing human error on calls with agonal breathing. In addition, there is the Speed vs Compliance Paradox, where even though AI detects OHCA 44 seconds faster than humans, the CPR process by officers does not significantly improve (25). This is related to trust and operator workload. The potential of AI is reflected in its ability as a multifunctional decision support system. Blomberg et al. (2019) reported an increase in OHCA detection sensitivity from 72.5% to 84.1% when AI was used, despite a lower positive predictive value (20.9% vs. 33.0%)(26). Darginavicius et al. (2023) proved that AI-based surveillance cameras achieved 95% sensitivity in detecting OHCA in public places, although their performance degraded at distances >15 metres (27). Scquizzato et al. (2023) revealed that ChatGPT was able to accurately answer 88.2% of OHCA questions, although the CPR content scored the lowest (64.8%) due to the complexity of the instructions (23). Another opportunity lies in integrating AI with wearable devices for early detection, as Kajino et al. (2024) proposed in optimising resuscitation protocols (22).

Key challenges include data privacy, ethical and technical issues, particularly in visual surveillance-based systems(27), and inconsistencies in historical datasets reduce the accuracy of neurological outcome prediction (29) (24). Limitations of integration with local protocols, such as interregional metadata variations (32), hinder the widespread adoption of AI. In addition, sample selection bias (25), and dependence on the quality of heart rhythm annotations(30), potentially reduce the potency and reliability of the AI models used. On the other hand, AI offers transformative solutions through large-scale retrospective analyses for mapping therapy response patterns, as demonstrated by Corti in improving real-time bystander CPR instruction. Multidisciplinary collaboration and external validation are key to the sustainable implementation of this technology in the emergency care system, especially out-of-hospital cardiac arrest.

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Table 2. A summary Review article is equipped with a matrix table

No	Study	Design	Country	Ai Description	Objective	Intervention	Result
1	(22)	Retrospective cohort study	Japan	Deep learning-based AI (Prediction One® software; neural network/ensemble learning; trained on 11 prehospital variables)	To develop and validate an AI-based TOR rule for predicting neurologically favorable outcomes in OHCA, and compare its performance to the Universal TOR rule	A deep learning model (Prediction One®) was developed using a national OHCA registry to predict outcomes after cardiac arrest. It was trained on over 149,000 cases and tested on more than 153,000. The model used 11 prehospital factors and identified the four most important (no ROSC, not witnessed by EMS, age over 68, asystole) to form a simplified AI-TOR rule. Its accuracy was then compared to the existing Universal TOR rule to evaluate performance..	1. The AI-TOR model performed with high accuracy: - AUC of 0.965 when using 11 variables - AUC of 0.952, even with just four key variables (AUC close to 1.0 indicates excellent prediction ability) 2. It outperformed the traditional universal TOR rule: - Specificity of 0.990 (vs. 0.959 for Universal TOR) - Positive Predictive Value (PPV) of 0.999 (vs. 0.998) 3. Very low risk of false prediction - Only 0.07% of patients who met all AI-TOR criteria had favorable neurological outcomes. - This shows the model is extremely accurate and clinically reliable for guiding decisions to stop resuscitation.
2	(23)	Cross-sectional evaluation (simulation/education)	United Kingdom (with international participants)	ChatGPT (OpenAI, March 14, 2023 version), a large language model AI chatbot	To assess the accuracy, clarity, relevance, comprehensiveness, and overall value of ChatGPT's answers to laypeople's questions about cardiac arrest and CPR	Forty CPR-related questions were answered by ChatGPT and reviewed by professionals and laypeople for accuracy, clarity, usefulness, and readability using the Flesch score.	1. Overall rating: Mean 4.3/5 (SD 0.7) 2. Professional vs Layperson: 4.0 vs 4.6 (p = 0.02) 3. Top-rated aspects: Clarity (4.4), Relevance (4.3), Comprehensiveness (4.2), Accuracy (4.0) 4. Lowest scores: Found in CPR-related questions 5. Readability: Median Flesch score = 34 ("Difficult") The results are generally good for most aspects, but for CPR-related questions, scores were lower, and there is a risk of inaccuracy. Statistically, there was a significant difference between professional and lay ratings, but overall, the results are positive and relevant.

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No	Study	Design	Country	Ai Description	Objective	Intervention	Result
3	(24)	Retrospective cohort study	Taiwan	AI model using support vector machine (SVM) and mel-frequency cepstral coefficients (MFCC) for audio emotion recognition	To develop an AI model for detecting a caller's emotional state during OHCA dispatch calls by processing audio recordings	Audio from 337 OHCA emergency calls (March–April 2011) was collected. Human raters classified the caller's emotion using the ECCS score. The audio was cleaned (noise removal, speaker separation), and MFCC features were extracted. An SVM model was trained to classify emotional stability (stable: ECCS 1–3; unstable: ECCS 4–5). The model's performance was tested using repeated random subsampling cross-validation (RRS-CV) on the full audio and the first 10 seconds of calls.	1. The AI model achieved high accuracy (92.26%) and specificity (98.29%) in detecting emotionally unstable callers using complete voice data. 2. Sensitivity for unstable cases was moderate (38.76%), with a positive predictive value (PPV) of 72.97%. 3. Using only the first 10 seconds of audio, accuracy (92.87%) and specificity (98.64%) remained high. 4. Early prediction improved sensitivity to 52.38% and PPV to 84.62%. These findings indicate the model is effective for early detection of emotional stability, particularly for stable cases, but further validation is needed for unstable cases.
4	(25)	Randomized clinical trial (double-masked, 2-group)	Denmark	Machine learning model using speech recognition software to analyze emergency calls in real-time	To examine how a machine learning model trained to identify OHCA and alert dispatchers during emergency calls affected OHCA recognition and response	The machine learning model automatically analyzed all calls to the emergency number 112 (equivalent to 911) in real-time. When the model identified a suspected OHCA, dispatchers in the intervention group received a visual alert on their screen. Dispatchers in the control group followed regular protocols without receiving alerts, though the model still analyzed their calls. The trial was conducted at Copenhagen Emergency Medical Services between September 2018 and December 2019.	1. No significant improvement in OHCA recognition: Dispatchers using AI alerts identified 93.1% (296/318) of confirmed OHCAs, compared to 90.5% (304/336) without alerts (P = .15). 2. Similar time-to-recognition: Mean recognition time was 1.72 minutes (intervention) vs. 1.70 minutes (control) (P = .90). 3. AI outperformed dispatchers: The machine learning model achieved higher sensitivity (85.0% vs. 77.5%; P < .001) but lower specificity (97.4% vs. 99.6%) and positive predictive value (17.8% vs. 55.8%) compared to human dispatchers (P < .001). While the AI performed better than humans at detecting OHCA, providing alerts to dispatchers did not significantly change their performance.
5	(26)	Retrospective Observational study.	Copenhagen, Denmark	Machine learning framework (Corti.ai), an ensemble of models for real-time	To determine if a machine learning framework could recognize OHCA	All emergency calls to Copenhagen EMS in 2014 (n=108,607) were retrieved. A machine learning framework	1. Out of 918 OHCA calls, ML framework recognized 772 (84.1%) vs dispatcher 665 (72.4%) (p<0.001).

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No	Study	Design	Country	Ai Description	Objective	Intervention	Result
				audio analysis of emergency calls	from audio files of emergency calls and compare its performance to that of medical dispatchers	was trained and validated to recognize OHCA from raw audio files. Its sensitivity, specificity, and PPV were calculated and compared to dispatcher performance. Time to recognition was also compared. Logistic regression identified factors influencing recognition.	2. ML had higher sensitivity (84.1% vs 72.5%, p<0.001), lower specificity (97.3% vs 98.8%, p<0.001), and lower PPV (20.9% vs 33.0%, p<0.001). ML recognized OHCA faster (median 44s vs 54s, p<0.001). ML missed fewer cases than dispatchers (10 vs 117). ML was more sensitive and faster, but had more false positives than dispatchers.
6	(27)	Experimental simulation study With a cross-sectional analytical approach.	Lithuania	YOLOv5 AI algorithm for fall detection using public surveillance cameras	To evaluate AI's potential in detecting OHCA-related falls and activating EMS in public spaces	Developed an AI model using YOLOv5 trained on simulated falls in a university corridor. Tested with 14 healthy volunteers performing falls at varying distances (near/far). Metrics: recall, precision, F1 score, mAP	1. Recall: 0.95 (detects 95% of falls) 2. Precision: 0.968 (96.8% true positives)F1 Score: 0.958 mAP: 0.978 3. Distance correlation: Fall detection accuracy decreases with distance from the camera (p<0.05). AI effectively detects falls in simulation, but performance decreases with distance from the camera.
7	(28)	Retrospective Observational Study	France	Machine learning models (logistic regression, random forest, neural network) for phonetic characteristics analysis of the caller's voice	Developing and evaluating ML models for detecting OHCA based on the phonetic characteristics of emergency callers' voices	Analysed 820 emergency call recordings (410 OHCA and 410 non-OHCA) from the Rennes Emergency Centre (2017-2019). Phonetic variables (fundamental frequency, formants, intensity, jitter, shimmer, etc.) were extracted using PRAAT software and WC-MDX Workstation. Three ML models were trained and tested.	1. Random forest performed best with AUC 74.9 (95% CI: 67.4-82.4). 2. Significant variables: pitch mean (p<0.001), formant H1/H2 (p<0.001), intensity med (p<0.001), jitter (p<0.001). 3. The phonetic characteristics of gulling sounds can distinguish OHCA, but the model performance is still moderate (AUC < 80).
8	(29)	Retrospective cohort study	USA Chicago	Model Embedded Fully Convolutional Network (EFCN) dengan 27 fitur input dari registri CARES	Develop an ML model to predict neurological outcome in OHCA and analyse the sensitivity of interventions (bystander CPR, coronary angiography, TTM)	The model was trained using data from 2,639 witnessed OHCA cases (2013-2016) from Chicago CARES. Sensitivity analysis was performed by modifying the intervention variables (bystander CPR → EMS, Yes/No coronary angiography). Validation using	1. EFCN Performance: AUC 0.9079 (CA) and 0.8967 (CPC). Sensitivity: 0.825 (class average). 2. Sensitivity Analysis: Additional bystander CPR saved 33 patients; additional coronary angiography saved 88 patients. The model effectively predicts outcomes and the' impact of interventions but needs external validation.

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No	Study	Design	Country	Ai Description	Objective	Intervention	Result
						60-15-25 split data (training-validation-testing).	
9	(30)	Retrospective cohort study	US, EU EMS	Deep learning (CNN, ResNet) with adaptive RLS filter for mechanical CPR artifact suppression	Develop an AI model for classifying 3 types of cardiac rhythms (Shockable/Sh, Asystole/AS, Organised/OR) during mechanical CPR using the LDB device.	1. Using data from the CIRC trial (2058 OHCA patients) 2. RLS filter with 35 harmonics (λ=0.989) to remove CPR artifacts 3. DL model training (CNN & ResNet) on 9,666 ECG segments 4. Validation on 5,813 segments with ground truth of artifact-free interval	1. ResNet Performance: - -Sh sensitivity: 90.6% - US Sensitivity: 84.2% - OR sensitivity: 88.3% - UMS: 88.3% - UMFS: 88.3% - Accuracy: 88.2% 2. ResNet outperformed CNN and RF, meeting AHA criteria (Se >90%, Sp >95%) for Sh/NSh detection. The model reduced false positives by 82.2% during mechanical CPR.
10	(31)	Pilot implementation study/ Project study	France & Italy	AI4EMS software: NLP-based system using deep learning for emergency conversation analysis	Evaluate AI's ability to detect OHCA during emergency calls and compare its performance with human officers.	1. AI model training using historical data of emergency calls (3265 calls in Italy, 2069 in France) 2. Real-time implementation of AI during emergency calls in emergency service centres 3. Performance validation with 5-fold cross-validation (Italy) and hold-out dataset (France) 4. Detection time and accuracy analysis	1. Recall AI vs Human: - Italy: +3.9% (AI 86.6% vs officer 82.7%) - France: +5.5% (AI 94.5% vs attendant 89%) 2. Detection Time: AI 2.5x faster on complex conversations (saving >2 minutes/intervention) False Positive Rate: 3.49% (Italy), 0.53% (France) 3. AI consistently outperforms humans in the speed and accuracy of OHCA detection

Abbreviations: AI - Artificial Intelligence; EMS - Emergency Medical System; OHCA - Out of Hospital Cardiac arrast; SVM - Support Vektor Machine; MFCC - Mel-Frequency Cepstral Coefficients; CPR – Cardio Pulmonary Resuscitation; NLP - Natural Language Processing; PPV - Positive Predictive Value; TOR – Termination Of Resuscitation; RLS - Recursive Least Squares; CNN - Convolutional Neural Network; ECG – Electrocardiogram; MI – Moicardial Infarction; GDPR - General Data Protection Regulation; EFCN - Embedded Fully Convolutional Network; LDB - Load Distributing Band; AHA – American Heart Association; YOLOv5 - You Only Look Once version 5; TTM – Targetted Temperature Management; RRS-CV - Repeated Random Sub-sampling Cross-Validation; RestNet – Residual Network; ML – Machine Learning; mAP – Mean Average Precition; ECCS – Emotion Content and Cooperation Score; CPC – Cerebral Performance Cathegor; RF – Random Forest.

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Table 3. Research Findings on Opportunities and Challenges in the Implementation of AI in OCHA

No	AI Category	Opportunity	Chalengges	Study
1	Deep learning-based AI (Prediction One® software; neural network/ensemble learning; trained on 11 prehospital variables)	- More accurate identification of futile resuscitation - Potential to reduce unnecessary hospital transports - Demonstrates the feasibility of AI in EMS clinical decision-making	- Need for external validation before clinical adoption - Ethical, legal, and cultural considerations in TOR implementation - Acceptability among EMS providers and families	(22)
2	ChatGPT (OpenAI, March 14, 2023 version), a large language model AI chatbot	- ChatGPT can be a quick and easily accessible source of information for the public about cardiac arrest and CPR. - Potential to improve public education and patient engagement and reduce healthcare provider workload. - Can be used to answer common questions with high satisfaction among lay users.	- Professionals often say that answers related to CPR were less accurate or less comprehensive. - Low readability (difficult for some segments of the public to understand). - Risk of "hallucination" (incorrect or unfounded answers), training data bias, and overreliance on AI. - Cannot provide references or updates after September 2021. - Privacy, data security, and ethics in healthcare AI use.	(23)
3	AI model using support vector machine (SVM) and mel-frequency cepstral coefficients (MFCC) for audio emotion recognition	- Enables rapid, automated identification of emotionally unstable callers in OHCA dispatch. - Can help dispatchers tailor communication strategies early, potentially improving dispatcher-assisted CPR. - Reduces manual workload and judgment fatigue for dispatch centers. - Early detection (within 10 seconds) is feasible and practical for real-time triage.	- Limited by small sample size and single-center data. - Sensitivity for unstable cases is moderate/low (risk of missed unstable callers). - Generalizability to other languages and EMS systems is unproven. - Requires further validation with larger, more diverse datasets. - Implementation in real-world dispatch workflow needs assessment.	(24)
4	Machine learning model using speech recognition software to analyze emergency calls in real-time	- The machine learning model could identify 54 additional OHCAs that dispatchers did not recognize - Model demonstrated consistent performance between retrospective and prospective evaluation, showing robustness - Potential for earlier recognition of OHCA, as the model could alert within 1.39 minutes from call onset - Could potentially improve survival rates if implementation barriers are addressed	- Poor dispatcher compliance with machine learning alerts - Dispatchers often did not trust or act on the alerts - High false positive rate (82.2% of suspected OHCA calls were false positives) - Complete compliance would have resulted in 1,519 additional ambulances dispatched unnecessarily (2.7% increase) - Human-computer interaction issues need to be addressed - Model needs improved specificity to increase	(25)

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No	AI Category	Opportunity	Chalengges	Study
			alert relevance and dispatcher trust - Insufficient dispatcher training on how to utilize the AI assistance	
5	Machine learning framework (Corti.ai), an ensemble of models for real-time audio analysis of emergency calls	- ML can support dispatchers for faster and more sensitive OHCA recognition - Potential to increase bystander CPR and improve survival - May be extended to other time-critical conditions (stroke, MI, sepsis)	- Lower PPV (more false positives) than the dispatcher - Model only predicts at end-of-call, not real-time - Needs validation in other EMS systems/languages - Lack of data on CPR quality and in-hospital care - Details of internal AI architecture not publicly available	(26)
6	YOLOv5 AI algorithm for fall detection using public surveillance cameras	- OHCA detection in seconds - Potential increase in survival rate in unwitnessed cases - - Can be integrated with public CCTV systems	- Simulation data (not yet validated in the real world) - Privacy issues regarding CCTV usage - Performance decreases at distances >5 meters - High implementation costs - Limitations of the YOLOv5 model in differentiating OHCA from regular falls	(27)
7	Machine learning models (logistic regression, random forest, neural network) for phonetic characteristics analysis of the caller's voice	- Integration of phonetic analysis with a semantic-based OHCA detection system - Potential to reduce 25% of undetected OHCA cases - Support for dispatchers under high stress conditions - Real-time application for emergency calls	- Model performance was moderate (AUC 74.9) - Retrospective study with limited data - Does not consider linguistic factors - Need external validation on different populations - Real-time implementation has not been tested	(28)
8	Model Embedded Fully Convolutional Network (EFCN) dengan 27 fitur input dari registri CARES	- Integration of ML models for clinical decision support - Potential to improve survival rates by optimising interventions - Can be used as a health system policy simulation tool	- Data limited to the Chicago population - Does not include CPR quality factors and EMS response times - Model generalisation needs external validation - Limitations of granular data (e.g., ECG, comorbidities)	(29)
9	Deep learning (CNN, ResNet) with adaptive RLS filter for mechanical CPR artifact suppression	- Allows rhythm analysis without stopping CPR - Potential increase in survival rate up to 52.3% - Integration with commercial defibrillators for real-time decision support - Consistent performance between retrospective and prospective data	- Need external validation in other EMS systems - Dataset limitations (only LDB devices) - Risk of misclassification in cases with low-complex QRS or residual artifacts - Real-time implementation requires	(30)

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No	AI Category	Opportunity	Chalengges	Study
			computational optimisation	
10	AI4EMS software: NLP-based system using deep learning for emergency conversation analysis	- Increase survival rate through early detection - Reduced emergency responder workload - Potential integration with global EMS systems - Scalability for different languages/cultures	- Limited dataset size and variability - GDPR/data privacy compliance required - Need for regular retraining and local adaptation - Resistance to technology adoption in some EMS - Performance may vary with language, call complexity, and data quality	(31)

Abbreviations: AI - Artificial Intelligence; EMS - Emergency Medical System; OHCA - Out of Hospital Cardiac arrast; SVM - Support Vektor Machine; MFCC - Mel-Frequency Cepstral Coefficients; CPR – Cardio Pulmonary Resuscitation; NLP - Natural Language Processing; PPV - Positive Predictive Value; TOR – Termination Of Resuscitation; RLS - Recursive Least Squares; CNN - Convolutional Neural Network; ECG – Electrocardiogram; MI – Moicardial Infarction; GDPR - General Data Protection Regulation; EFCN - Embedded Fully Convolutional Network; LDB - Load Distributing Band; RestNet – Residual Network.

DISCUSSION

This study successfully identified opportunities and challenges in implementing Artificial Intelligence (AI) in Out-of-Hospital Cardiac Arrest (OHCA) management, highlighting the significant potential of AI in addressing research gaps related to real-world validation. EENA & Corti's (2020) pilot project in France and Italy demonstrated that integrating AI in dispatch systems improved OHCA detection by 5.5% and 3.9% in both countries, with identification times 2 minutes faster than humans (31). Although hampered by local protocol variations and limited historical data, this aligns with the theory in Greenhalgh et al. (2019), which states that health technology adoption requires adjustments to the local system (33). Nonetheless, external validation of AI models, such as the AI-TOR (22), with an AUC of 0.952, shows that models trained on heterogeneous data can overcome geographical bias, confirming the importance of multidisciplinary collaboration between researchers, clinicians, and regulatory decision-makers for the continued implementation of this technology.

Integrating AI in non-medical bystander training and mentoring faces challenges regarding instruction complexity, as seen in the lowest ChatGPT score in CPR content (64.8%). However, the analysis of Rafi et al. (2022) identified the potential of phonetic parameters (fundamental frequency and voice intensity) as bystander stress markers that can be optimised in AI-based interactive training (28). Gamification and real-time simulation approaches can improve retention of CPR skills in the lay public (34,35). In addition, the pilot project of EENA, Corti (2020), and Murk et al. (2023) emphasised the importance of instant feedback from AI to improve compression techniques. However, the trust factor in automated systems needs to be addressed through structural education (16)(31). AI has the potential to transform the role of a bystander into a more competent and prepared first responder.

Ethical issues and data governance are important aspects of AI implementation in OHCA. Darginavicius et al. (2023) underlined the privacy risks in visual surveillance-based systems, especially in light of the GDPR in Europe. The application of the privacy-by-design principle can address this issue by ensuring data anonymisation without compromising model accuracy(27,36,37). In addition, biases in the historical dataset, such as inaccuracies in the annotation of heart rhythms (24), may exacerbate algorithmic unfairness on minority populations. Harford et al. (2019) recommend auditing multidemographic datasets and external validation to reduce this bias. Collaboration with independent ethics bodies is necessary to balance innovation with accountability (29).

The paradox between speed and compliance in dispatcher response to AI alerts is an important challenge. Blomberg et al. (2019) showed that technical improvements in AI systems do not automatically change human behaviour. In this regard, the concept of human-AI teaming, which emphasises the importance of interface design that prioritises clarity of recommendations and trust-building of human-AI

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collaboration, is a key issue (38) (26). In addition, the study of Isasi et al. (2025) showed that RLS adaptive filters can reduce mechanical compression noise by up to 95%, but over-reliance on AI risks automation bias. Training dispatchers with mixed-initiative scenarios, where AI serves as a second opinion, can optimise decision-making without neglecting the human role in the process (30).

An interesting finding from this study was that the heart rhythm classification model can remain effective despite variations in compression depth (±15%). This finding opens up opportunities to integrate AI with wearable devices to detect OHCA early. However, Kajino et al. (2024) cautioned that the increased workload of officers due to false positives from AI could disrupt emergency workflows. This approach aligns with the suggestion of Seng et al. (2025), who emphasise the importance of energy-efficient, on-the-ground AI system design (22,39,40). To address the gap in AI implementation in real-world OHCA cases, external validation of AI models across different populations and local contexts is a priority. The study of Kajino et al. (2024) showed that the AI-TOR model can be adapted with 99% specificity into regional protocols through multidisciplinary collaboration between clinicians, researchers, and regulators. In addition, the EENA & Corti (2020) pilot project proved that AI integration in existing dispatch systems can improve OHCA detection, although it requires metadata customisation(22,31). Developing context-aware AI-based adaptive algorithms that consider local protocol variations, as Blomberg et al. (2021) suggested, may reduce operational barriers in AI implementation in OHCA (25).

On the other hand, in non-medical bystander training and mentoring, the integration of AI-based voice analysis (28) can produce interactive modules with real-time feedback that improve CPR techniques. In addition, wearable devices connected with AI (30) provide visual and auditory guidance for bystander optimisation of compression depth and frequency. In the face of ethical and data governance issues, applying privacy by design principles and multimodal data anonymisation is an important solution to maintain safety and accuracy. AI implementation in emergency care systems, especially in OCHA cases, can achieve better clinical and operational sustainability by following these recommendations. The gaps identified in the literature have been addressed through the transformative findings in this study. AI implementation is not only feasible but also has the potential to improve OHCA survival rates if supported by multidisciplinary collaboration and ethical data infrastructure. Adopting the above recommendations allows AI integration in emergency care systems to achieve clinical and operational sustainability.

Strengths and Limitations of the Study

This review has certain limitations. Firstly, Heterogeneity of AI Applications, where the reviewed studies utilise various AI models (such as machine learning, deep learning, and CNN) with different objectives, ranging from voice-based OHCA detection to heart rhythm classification. This variation makes it difficult to directly compare the effectiveness of models. Secondly, the lack of large-scale and long-term experimental studies hinders the understanding of the impact of AI on OHCA outcomes, especially in varied non-clinical settings. Thirdly, variability in the acceptance and implementation of AI technologies in EMS systems due to cultural differences, costs, and resistance from healthcare professionals also adds to the complexity.

Despite these limitations, this Review has a comprehensive scope integrating nine articles and 1 Pilot project report from 10 countries (France, Italy, Japan, Lithuania, Denmark, USA, Taiwan, Japan, UK and Spain), highlighting AI applications ranging from voice analysis to wearable devices, thus providing a global perspective. Additionally, this research evaluates various technological and human aspects, including AI-based systems, dispatcher protocols, bystander training, and ethical issues. This multidimensional approach enriches the findings and provides valuable insights into the practicality of AI integration into emergency medical services (EMS). Moreover, the focus on recent innovations, such as AI-based interventions for bystander training and gamification in training, highlights how AI can bridge the gap between technology and public health response. These findings are also balanced by using varied study designs, cohort studies, retrospective studies, experimental observational research, randomised controlled trials, and pilot project reports, offering a well-rounded perspective and ensuring a deeper understanding of recent developments in the field. The combination of limitations and strengths of these studies provides a complete map of the literature. It directs future research priorities to ensure AI can be implemented ethically, effectively, and sustainably in the management of OHCA.

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CONCLUSION

Analysis of 9 articles and one pilot project suggests that implementing Artificial Intelligence (AI) in Out-of-Hospital Cardiac Arrest (OHCA) management has significant potential to improve early detection, speed up emergency response, and support more informed clinical decisions. The findings of this study indicate that AI can improve OHCA detection sensitivity, reduce EMS response time, and reduce resuscitation errors. In addition, this technology can potentially increase the effectiveness of bystander interventions, which could contribute to improved survival rates for OHCA victims. However, challenges such as data privacy, inconsistency of local protocols, and reliance on data quality remain key barriers to the real-world implementation of this technology. Interesting findings, such as the paradox of speed and compliance, provide a basis for further research on human-AI teaming in emergencies, especially out-of-hospital cardiac arrest cases.

The benefits of the findings of this study are highly relevant both theoretically and practically in the field of critical care nursing, especially in the management of OHCA cases. Theoretically, this study provides deeper insights into the potential and challenges of AI integration in the emergency system, while opening up opportunities for further research on adapting AI models in various local contexts. Practically, the findings offer solutions for improving the quality of training and mentoring of non-medical bystanders, which can strengthen the first response in OHCA events. Improving the understanding of AI in critical care practice, this technology can assist medical personnel, including critical care nurses, in making more informed and rapid decisions. Nonetheless, we recognise the limitations of this study, especially related to the variety of AI technologies used and the lack of long-term studies. We recommend future research to focus on the validation of AI models in various populations and local contexts and the development of more adaptive algorithms to face the challenges of varying protocols in different regions.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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