

Artificial Intelligence in Cardiopulmonary Resuscitation: Revolutionizing Resuscitation Through Precision and Prediction – A Narrative Review

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Abstract: Cardiopulmonary resuscitation (CPR) remains a fundamental intervention in the management of cardiac arrest, with timely initiation and optimal performance serving as critical determinants of survival and neurological recovery. In recent years, the application of artificial intelligence (AI) has emerged as a promising approach to enhance the effectiveness of CPR by delivering real-time feedback, supporting clinical decision-making, and enabling individualized resuscitation strategies. This narrative review summarizes the current applications of AI in CPR, including rhythm interpretation, quality monitoring, and post-resuscitation care. In addition, it discusses major challenges related to data privacy, system interoperability, algorithmic fairness, and ethical governance. Future directions emphasize the importance of interdisciplinary collaboration, rigorous model validation, and structured training for clinical users. Although additional validation is required, the integration of AI into resuscitation practices holds significant promise for enhancing patient outcomes and potentially reducing mortality associated with sudden cardiac arrest.

Keywords: artificial intelligence, cardiopulmonary resuscitation, cardiac arrest, machine learning, clinical decision-making, emergency medicine, resuscitation outcomes

Introduction

Sudden cardiac death (SCD) is a major global public health challenge, accounting for 15–20% of all mortality and causing approximately 4–5 million deaths annually, representing nearly half of all cardiovascular-related fatalities.^{1–3} Cardiopulmonary resuscitation (CPR) remains the cornerstone of management for cardiac arrest, with timely initiation and high-quality performance being critical for survival and favorable neurological outcomes.^{4,5} Despite advancements in resuscitation science, survival rates for out-of-hospital cardiac arrest (OHCA) remain low, often below 10% in many regions, underscoring the urgent need for innovative approaches.¹ Variability in CPR quality, driven by factors such as rescuer fatigue and inconsistent training, further complicates achieving optimal outcome.^{6–8} These challenges highlight the critical need to integrate advanced technologies to enhance the effectiveness of resuscitation efforts.

Artificial intelligence (AI) and machine learning (ML) have transformed many areas of medicine; however, their application in CPR remains at an early stage of development.⁹ Current evidence supports the utility of AI and ML in enhancing CPR, particularly through real-time feedback on compression depth, rate, and recoil, which improves performance consistency, as well as rhythm analysis algorithms integrated into automated external defibrillators (AEDs), which have demonstrated superior accuracy in detecting shockable rhythms.^{10–12} More exploratory applications, such as fully individualized resuscitation strategies based on patient-specific physiological profiles and predictive analytics aimed at forecasting long-term survival or neurological recovery, remain largely conceptual and require rigorous clinical validation.^{13,14} Innovative approaches such as AI-driven wearable devices, telemedicine platforms, and federated learning techniques for secure data processing show promise for real-time cardiac arrest detection and decision support; nevertheless,

robust large-scale clinical evidence demonstrating their impact on patient outcomes is currently lacking.^{12,15,16} Emerging data suggest that AI may improve resuscitation outcomes by providing real-time guidance and addressing limitations inherent to conventional CPR practices.^{10,14} However, the extent to which these technologies can optimize CPR performance and reduce mortality among patients with cardiac arrest warrants further investigation.

AI-driven technologies offer promising opportunities to enhance CPR by providing real-time feedback on key performance metrics, including compression depth, rate, and chest recoil, and by enabling personalized resuscitation strategies that account for patient-specific factors such as medical history and physiological data.^{10–13} Furthermore, integrating predictive analytics into platforms such as AEDs, wearable devices, and emergency medical services (EMS) can support clinical decision-making and improve both individual and system-level resuscitation responses.^{9,17} Collectively, these innovations have the potential to improve survival rates and neurological outcomes in patients experiencing cardiac arrest.

This narrative review examines the role of AI in CPR, with a particular focus on its applications in real-time feedback, clinical decision support, and personalized care approaches. It provides a comprehensive overview of current AI applications in CPR, including rhythm interpretation, quality monitoring, and post-resuscitation management, while addressing key challenges related to data privacy, system interoperability, algorithmic fairness, and ethical governance. In addition, it explores future directions for integrating AI into clinical practice, emphasizing the need for interdisciplinary collaboration, rigorous model validation, and structured training to maximize its impact on cardiac arrest outcomes.

Material and Methods

A structured approach was applied to synthesize the literature on applications of AI in CPR. A comprehensive search of PubMed, Scopus, and Web of Science was performed using keywords and Medical Subject Headings (MeSH), including “artificial intelligence”, “machine learning”, “cardiopulmonary resuscitation”, and “cardiac arrest”. The search was restricted to English-language publications from 2015 to 2025. Studies with large cohorts or those reporting direct clinical outcomes, such as survival rates or neurological recovery, were prioritized to align with the research objective of improving CPR outcomes. Eligible studies included original research, scoping or systematic reviews, and clinical guidelines addressing AI applications in CPR, with a focus on rhythm interpretation, quality monitoring, or post-resuscitation care. Non-human studies were included only when findings were directly relevant to clinical applications, while editorials, opinion pieces, and studies without full-text availability were excluded.

Titles and abstracts were independently screened by two reviewers, followed by full-text assessment for eligibility. Discrepancies were resolved through consensus. Data extracted from the included studies, such as study design, sample size, AI application, and reported outcomes, were synthesized qualitatively. The findings were organized into thematic sections to highlight key applications, identify challenges, and inform future directions for the integration of AI in CPR.

Results

The Potential of AI in CPR

AI is increasingly recognized for its potential to enhance CPR by improving clinical decision-making, compression quality, and emergency response systems. Several emerging technologies illustrate AI’s transformative capacity. For example, AI-guided drones have been developed to expedite the delivery of AEDs in rural areas, reducing response times and improving survival rates in OHCA.¹⁸ Similarly, AI-driven CPR robots tested in preclinical porcine models achieved hemodynamic parameters, such as coronary perfusion pressure (CPP) and end-tidal carbon dioxide (ETCO₂), comparable to established devices like the Lund University Cardiopulmonary Assist System version 3 (LUCAS 3), demonstrating the feasibility of automated resuscitation.^{19,20}

Furthermore, Semeraro et al (2024) highlighted the role of AI in advancing resuscitation training by providing real-time feedback and simulation-based instruction, thereby improving system-wide preparedness.²¹ Alamgir et al (2021) demonstrated AI’s ability to facilitate early cardiac arrest detection through analysis of vital signs and electrocardiographic data, enabling timely intervention.²² AI has also been employed to support CPR quality assessment in both training and clinical settings, using biomechanical sensors to deliver immediate feedback on compression accuracy and enhance rescuer performance.²³

When integrated across the resuscitation continuum, from early recognition to post-resuscitation management, these innovations help address persistent limitations of conventional CPR, including provider variability and environmental challenges. By incorporating predictive analytics, immersive training modalities, and advanced delivery systems, AI can optimize the resuscitation process, providing scalable and effective solutions to improve clinical outcomes in cardiac emergencies worldwide. A summary of recent studies exploring various AI applications in CPR is presented in [Table 1](#).

Table 1 Summary of Recent Studies on Artificial Intelligence Applications in Cardiopulmonary Resuscitation

Author (Year)	Study Design	N (Total Patients)	Outcome Measured	Results & Observations	Additional Notes
Blomberg et al, (2019) ²⁴	Observational	108,607 emergency calls (918 cardiac arrest cases)	Early recognition of cardiac arrest during emergency calls	A machine learning framework demonstrated higher sensitivity (84.1% vs 72.5%) but slightly lower specificity (97.3% vs 98.8%) compared with dispatchers. Positive predictive value was lower (20.9% vs 33.0%). Median recognition time was shorter with AI (44s vs 54s, $p < 0.001$).	Focused on prehospital emergency call systems; directly compared AI with dispatcher performance in identifying out-of-hospital cardiac arrest (OHCA).
Di Mitri et al, (2019) ²⁵	Experimental / Training Study	11 medical students	Detection of CPR mistakes (compression rate, depth, release, arm position, body position)	Multimodal data (Kinect + Myo + manikin) enabled accurate mistake detection. Neural networks classified errors effectively; arm and body position errors were detected automatically, previously only identifiable by instructors.	Each participant completed two sessions of 2-minute chest compressions (5,254 compressions labeled). A questionnaire collected feedback for future system improvements.
Al-Dury et al, (2020) ²⁶	Retrospective cohort	45,000 patients	Survival prediction in OHCA	Random forest models identified initial rhythm as the strongest predictor of 30-day survival, followed by age, time to CPR, EMS response time, and place of arrest. Model accuracy reached 82.1% (10-fold cross-validation).	Swedish registry-based data; used permutation accuracy importance to rank 16 predictors; partial dependence plots visualized associations.
Alamgir et al, (2021) ²²	Scoping review	Not applicable	Early detection of cardiac arrest	AI technologies, primarily machine learning (81% of studies) and neural networks (49%), predicted cardiac arrest by analyzing patient parameters (55%), developing warning systems (34%), or distinguishing high-risk patients (11%). Most datasets had <10,000 samples (68%).	Registry-based study (Sweden); permutation accuracy importance ranked 16 predictors; partial dependence plots illustrated associations.
Wong et al (2022) ²⁷	Retrospective cohort / Validation study	5,970 patients	Survival to 30 days or hospital discharge after ROSC in OHCA	Most studies applied machine learning (81%) and neural networks (49%) to predict cardiac arrest by analyzing patient parameters (55%), developing early warning systems (34%), or identifying high-risk patients (11%). The majority used datasets with <10,000 samples (68%).	Included 47 studies (2013–2021). Emphasized the need for research addressing barriers to clinical implementation.

(Continued)

Table 1 (Continued).

Author (Year)	Study Design	N (Total Patients)	Outcome Measured	Results & Observations	Additional Notes
Baumgarten et al (2022) ¹⁸	Simulation study	46 simulated OHCA scenarios (10 flights per route)	AED delivery time in rural areas	UAS-AED delivery achieved median alert-to-defibrillation times of 6:02 (0.4 km), 6:53 (2.29 km), 8:54 (4.0 km), 14:51 (7.43 km), and 15:51 min (9.79 km). All AEDs were retrieved safely within seconds of landing.	Conducted in rural Northeast Germany; integrated unmanned aerial systems with first-responder dispatch. Autonomous flights required pilot support for landing.
Okada et al (2023) ¹³	Narrative review	Not specified	AI and ML applications in resuscitation	AI and ML models, using structured (eg, demographics, biomarkers) and unstructured data (eg, ECG, EEG), demonstrated potential to optimize diagnosis, triage, and treatment.	Illustrated challenges of data quality, clinical integration, and risks of self-fulfilling prophecies. Highlighted prediction models, NLP, treatment heterogeneity, and reinforcement learning.
Agel et al (2023) ²⁸	Comprehensive review	Not specified	AI and ML applications in SCA prediction and CPR management	AI/ML, particularly deep learning, enhanced prediction of sudden cardiac arrest and improved CPR outcomes by refining AED rhythm detection and risk stratification.	Focused on prehospital emergency care. Discussed deep learning applications in radiomics, OHCA recognition, and COVID-19 outcomes.
Viderman et al (2023) ¹⁰	Scoping review	1,817,419 patients (59 studies)	AI applications in resuscitation (prediction, rhythm detection, outcomes, drone delivery)	AI methods outperformed conventional approaches in early warning, rhythm detection, dispatcher notification, and drone-delivered defibrillation. Demonstrated benefits in continuous patient monitoring.	Comprehensive synthesis across multiple clinical and prehospital settings.
Semeraro et al (2024) ²¹	Exploratory review	N/A	Technological innovations in cardiac arrest management	AI tools (eg, ChatGPT-4, Gemini Advanced) predicted implementation timelines of 3–8 years for future innovations, including wearable AEDs, robot-assisted CPR, and brain-computer interfaces.	Emphasized ethical challenges, particularly privacy and equity. Discussed potential applications across early recognition, CPR, defibrillation, and post-resuscitation care.
Cha et al (2024) ¹⁹	Experimental / Preclinical	12 pigs	Hemodynamic outcomes (CBF, CPP, ETCO ₂) and ROSC during CPR	AI-driven robotic CPR achieved comparable cerebral blood flow, coronary perfusion pressure, end-tidal CO ₂ , and ROSC rates relative to LUCAS 3. AI prediction of CBF showed excellent accuracy (Pearson $r=0.98$).	Porcine model of VF-induced cardiac arrest. Robot dynamically optimized compression position, depth, and rate during the first 270 s using biosignal-sensitive feedback.

Abbreviations: AED, Automated External Defibrillator; AI, Artificial Intelligence; CBF, Cerebral Blood Flow; COVID-19, Coronavirus Disease 2019; CPP, Coronary Perfusion Pressure; CPR, Cardiopulmonary Resuscitation; ECG, Electrocardiogram; EEG, Electroencephalogram; EMS, Emergency Medical Services; ETCO₂, End-Tidal Carbon Dioxide; LUCAS 3, Lund University Cardiopulmonary Assist System, version 3; N/A, Not Applicable; OHCA, Out-of-Hospital Cardiac Arrest; ROSC, Return of Spontaneous Circulation; SCA, Sudden Cardiac Arrest; UAS, Unmanned Aerial System; VR/AR, Virtual Reality / Augmented Reality; VF, Ventricular Fibrillation.

The Role of AI Platforms in Transforming CPR Programs

AI platforms enhance CPR programs through improvements in the effectiveness of emergency interventions. A major contribution lies in the early detection of cardiac arrest. Analysis of emergency call audio and digital signals enables AI systems to identify critical indicators and deliver real-time CPR instructions to bystanders, which increases intervention rates

and improves survival outcomes in OHCA.²⁴ This capability is particularly important for strengthening bystander CPR, a decisive factor in patient survival.

AI also contributes substantially to optimizing CPR quality during both training and clinical practice. Data obtained from video, audio, and biomechanical sensors allow AI systems to provide immediate feedback on chest compression accuracy, thereby enhancing rescuer performance and supporting competency development among healthcare professionals.²⁵ The influence of AI extends across the entire chain of survival, from early recognition of cardiac arrest to post-resuscitation care. For instance, AI-enabled drones have been deployed to accelerate the delivery of AEDs, reducing response times in rural settings and improving survival rates.²⁹ Semeraro et al (2024) emphasized the role of AI in advancing resuscitation training through real-time feedback and simulation, thereby strengthening preparedness across healthcare systems.

The effective integration of AI into CPR programs requires the use of comprehensive multimodal datasets, including emergency call recordings and sensor outputs, to ensure optimal performance.²⁴ In addition, ethical, legal, and regulatory considerations are essential to guarantee the responsible and equitable implementation of AI technologies in resuscitation.³⁰ Through enhanced early detection, improved CPR quality, and system-wide coordination, AI platforms have the potential to transform the resuscitation continuum and deliver better survival and neurological outcomes for patients experiencing cardiac arrest.

Challenges in Implementing AI in CPR

Despite its transformative potential, implementing AI in CPR presents considerable challenges. A key barrier lies in its integration into existing healthcare systems. Many hospitals and emergency medical services (EMS) lack the necessary digital infrastructure, requiring substantial investments in advanced technologies, workforce training, and adaptation of clinical protocols. Global disparities in healthcare resources and expertise further complicate the equitable adoption of AI across different settings.¹⁸

In low- and middle-income countries (LMICs), where more than 80% of global cardiac arrests occur outside hospital environments, the integration of AI into CPR programs faces significant barriers that compromise equitable access.³¹ In sub-Saharan Africa, unreliable electricity supply and limited internet infrastructure hinder real-time AI applications. For instance, a study conducted in rural Kenya reported that AI-assisted drone delivery of AEDs achieved only a 60% success rate, with power outages and connectivity failures affecting over 70% of cases in remote regions.³² Across South Asia, evidence from India demonstrates that AI-enabled wearable devices can enhance bystander CPR in densely populated urban slums, reducing response times by approximately 25% in cohorts exceeding 500 participants. However, because training datasets are predominantly derived from urban populations, algorithmic accuracy decreased by nearly 30% among rural ethnic groups, thereby exacerbating existing geographic inequities.³³ In Latin America, economic constraints create further obstacles to scalability. A Brazilian evaluation of AI-driven rhythm analysis within public EMS revealed unit costs exceeding \$500, restricting deployment to wealthier regions and leaving underserved communities dependent on manual CPR, with survival rates approximately 15% lower than those in areas with AI support.³¹ Collectively, these regional case studies highlight the urgent need for context-specific strategies such as offline-capable algorithms, infrastructure-appropriate technologies, and locally adapted training programs to bridge the gap between innovations developed in high-income settings and the realities of LMIC healthcare systems.

Another major challenge involves validating AI applications in real-world environments. Emergency situations are characterized by variable data quality, environmental noise, and unpredictable patient responses, all of which can undermine algorithmic reliability.³⁴ Rigorous clinical trials and ongoing performance monitoring are therefore essential to ensure the safety, accuracy, and effectiveness of AI in high-stakes resuscitation contexts.²²

Ethical and legal considerations represent additional critical obstacles. Assigning responsibility for adverse outcomes in life-threatening circumstances raises complex medico-legal and moral questions.²³ Moreover, the performance of AI systems depends heavily on the quality and representativeness of training datasets. Biased or incomplete datasets risk reinforcing existing healthcare inequities or generating unreliable outputs.¹⁹ Equally important is healthcare provider acceptance: in time-sensitive resuscitation scenarios where clinical judgment is paramount, providers may hesitate to rely on AI due to skepticism or concerns regarding automation bias.²¹ Promoting AI as a supportive adjunct to, rather than a replacement for, human expertise is essential to foster trust and encourage adoption. [Table 2](#) outlines the principal challenges associated with implementing AI in CPR.

Table 2 Principal Challenges in Implementing AI in Cardiopulmonary Resuscitation and Proposed Solutions

Challenge	Description	Impact	Proposed Solution	Reference
Integration into Clinical Systems	Limited digital infrastructure within EMS and hospital settings impedes AI deployment.	Delays in real-time AI feedback during CPR, reducing response efficiency and care quality.	Invest in HIT infrastructure and provide targeted training for EMS and hospital personnel.	[22,35]
Lack of Real-World Validation	AI demonstrates strong performance in controlled environments but struggles under variable clinical conditions.	Unreliable AI outputs in emergencies may disrupt CPR delivery and erode clinician trust.	Conduct large-scale, multicenter clinical trials and establish continuous performance monitoring frameworks.	[35]
Ethical and Legal Concerns	Uncertainty regarding accountability for AI-related adverse outcomes.	Hesitancy to adopt AI tools during CPR due to medico-legal risks and liability concerns.	Develop robust regulatory frameworks and ensure transparent AI decision-making processes.	[36,37]
Data Bias and Quality Issues	Biased or incomplete training datasets compromise AI predictive accuracy.	Inaccurate rhythm detection or CPR feedback, increasing the risk of suboptimal outcomes.	Employ diverse, representative datasets and conduct regular algorithmic audits.	[37]
Healthcare Staff Resistance	Clinician skepticism toward AI in high-pressure resuscitation scenarios.	Underutilization of AI tools, limiting potential improvements in CPR quality and decision-making.	Promote AI as a supportive adjunct through structured training, education, and trust-building initiatives.	[36]

Abbreviations: AI, Artificial Intelligence; CPR, Cardiopulmonary Resuscitation; EMS, Emergency medical services; HIT, Health Information Technology.

AI in CPR Staff Training and Readiness

Integrating AI into CPR training enhances clinical team preparedness while presenting specific challenges. Effective implementation necessitates continuous training for physicians, nurses, and emergency responders to ensure the competent and safe utilization of AI tools. Even brief structured exposure such as one-hour hands-on sessions has been demonstrated to substantially enhance clinicians' confidence and operational efficiency, reducing workload and facilitating timely decision-making during high-pressure CPR scenarios.^{19,35} To support both immediate adoption and sustained proficiency, many healthcare organizations have incorporated AI-focused modules into professional development programs.

Embedding AI within clinical workflows also requires robust governance protocols, including continuous system monitoring and real-time evaluation of AI outputs to ensure accuracy and safety during critical interventions.²³ Furthermore, AI is transforming CPR education through immersive technologies. Virtual and augmented reality (VR/AR) platforms provide personalized, data-driven feedback, enabling physicians, nurses, and trainees to achieve higher accuracy and improved skill retention compared with conventional methods.³⁰ These innovations enhance procedural competence, adaptability, and preparedness, cultivating a resilient and technologically proficient healthcare workforce and ultimately supporting improved patient outcomes in cardiac emergencies.

Data Privacy and Security in AI-Driven CPR

The deployment of AI in CPR requires stringent measures to safeguard data privacy and security. AI systems rely on sensitive datasets, including biometric indicators, electrocardiographic recordings, and geolocation information collected during emergency scenarios. Maintaining the confidentiality, integrity, and availability of these data is critical, particularly in real-time AI-supported interventions. Unauthorized access or data breaches can create ethical and legal risks and undermine public trust in AI applications within healthcare.³⁰

Robust data protection strategies are therefore essential. End-to-end encryption, role-based access controls, and regular security audits mitigate cyber threats while ensuring system reliability in clinical settings. Compliance with

international regulations, including the General Data Protection Regulation (GDPR) in the European Union and the Health Insurance Portability and Accountability Act (HIPAA) in the United States (US), requires de-identification of patient information and informed consent, particularly when data are used for AI model development and training.³⁰ Emerging approaches, such as federated learning, enhance privacy by allowing AI models to be trained on decentralized datasets without transferring raw patient data, preserving model performance while minimizing risks.³⁵ Clear accountability among healthcare institutions, AI developers, and data custodians is essential to uphold ethical standards throughout the AI lifecycle. Strong security measures and adherence to regulatory requirements further protect sensitive data and foster trust in AI-driven CPR systems, ultimately supporting safer and more effective patient care.

Regulatory and Legal Frameworks for AI in CPR

The integration of AI into CPR requires comprehensive regulatory and legal frameworks to ensure safety, efficacy, and compliance. AI-driven tools, classified as Software as a Medical Device (SaMD), are subject to rigorous pre-market evaluation and post-market surveillance by regulatory agencies such as the US Food and Drug Administration (FDA), Health Canada, and the European Union's AI Office.²⁵ The European Union's AI Act, effective March 2024, designates healthcare AI applications as high-risk, imposing strict requirements for transparency, human oversight, risk assessment, and traceability throughout the AI lifecycle.³⁰

Achieving global regulatory harmonization remains challenging due to significant variations across jurisdictions and limited intergovernmental coordination.³⁸ To ensure compliance, developers and healthcare institutions must adopt Good Machine Learning Practices (GMLP) and predefined change control protocols, aligning with international initiatives such as the International Medical Device Regulators Forum (IMDRF) and the US–EU AI Code of Conduct.³⁹ Implementation of server-side logs, audit trails, and real-time system monitoring enhances accountability and supports regulatory reporting, fostering trust in AI applications. These regulatory and legal measures ensure that AI tools used in cardio-pulmonary resuscitation adhere to safety and ethical standards, thereby promoting effective patient care and sustaining public confidence in AI-driven interventions.

Equity and Access in AI-Driven CPR

AI has the potential to improve access to CPR, particularly in low-resource and remote settings; however, significant equity challenges persist. Many algorithms are developed using datasets derived primarily from high-income, urban healthcare systems, which often underrepresent diverse demographic and clinical populations. This lack of inclusivity limits algorithm generalizability and heightens the risk of suboptimal performance in rural or underserved areas.²⁵ As a result, such disparities may widen existing healthcare inequities and increase the likelihood of misdiagnosis or inappropriate clinical decision-making in underrepresented groups.^{30,38}

Limited digital infrastructure and the scarcity of AI-compatible devices in low-income regions further constrain the implementation of AI-driven CPR systems.³⁹ Bridging these gaps requires inclusive data collection and the development of context-sensitive algorithms validated across diverse clinical and geographic settings. Public–private partnerships may help expand telehealth infrastructure, bridge digital divides, and facilitate wider access to AI technologies. International organizations, including the World Health Organization (WHO) and the Organisation for Economic Co-operation and Development (OECD), stress that ethical AI deployment must prioritize fairness, inclusivity, and equitable access.³⁸ Implementing these principles is essential for ensuring that AI-driven CPR systems improve outcomes globally, reduce disparities, and foster trust in healthcare technology.

Interoperability and System Integration for AI in CPR

The effective implementation of AI in CPR depends on seamless interoperability across diverse healthcare systems. Efficient data exchange, standardized interpretation, and real-time responsiveness are critical for AI-enhanced resuscitation. Protocols such as Health Level Seven (HL7) and Fast Healthcare Interoperability Resources (FHIR) enable reliable data sharing across electronic health records (EHRs), EMS, and medical devices, including defibrillators, which supports timely clinical decision-making during cardiac emergencies.²⁵ AI-enabled tools that transform HL7 messages into FHIR resources further improve data accuracy and processing efficiency.³⁰

Table 3 Interoperability Requirements for AI-Powered CPR Systems

Configuration	Purpose / Benefit	Standard / Example	Reference
HL7 FHIR & Related APIs	Facilitate seamless data exchange between EHRs, EMS, and AI platforms to enable real-time decision support during CPR.	FHIR R4, SMART on FHIR	[41]
SNOMED-CT and LOINC vocabularies	Ensure standardized clinical terminology and data representation, supporting accurate and interoperable AI-driven decision-making in CPR contexts.	SNOMED-CT (diagnoses); LOINC (laboratory data)	[42]
ISO/IEEE 11073 Device Communication	Enable real-time transmission of physiological data from medical devices to AI systems during CPR, ensuring timely analysis and feedback.	ISO/IEEE 11073–20,601 (ECG, SpO ₂)	[40]

Abbreviations: CPR, Cardiopulmonary Resuscitation; ECG, Electrocardiogram; EHR, Electronic Health Record; EMS, Emergency Medical Services; FHIR, Fast Healthcare Interoperability Resources; HL7, Health Level Seven International; ISO/IEEE 11073, International Organization for Standardization / Institute of Electrical and Electronics Engineers 11073; LOINC, Logical Observation Identifiers Names and Codes; SMART on FHIR, Substitutable Medical Applications and Reusable Technologies on Fast Healthcare Interoperability Resources; SNOMED-CT, Systematized Nomenclature of Medicine—Clinical Terms; SpO₂, Peripheral Capillary Oxygen Saturation.

Semantic interoperability ensures consistent interpretation of clinical information across platforms. Standardized vocabularies, including Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) and Logical Observation Identifiers Names and Codes (LOINC), embedded within FHIR resources, promote uniform data structures that maintain AI reliability in varied clinical settings.³⁸ Compliance with FHIR Release 4 guidelines further enhances data harmonization across hospital and community environments.³⁹ Device integration supported by standards such as ISO/IEEE 11073–20601 enables plug-and-play connectivity for devices such as electrocardiogram (ECG) monitors, allowing real-time transfer of physiological data to AI platforms.⁴⁰ Adopting HL7 FHIR, standardized terminologies, and device communication protocols allows AI systems to operate cohesively, ultimately improving precision and timeliness in resuscitation efforts. Table 3 presents the key interoperability requirements for AI-driven CPR systems.

Discussion

This narrative review synthesizes the evolving applications of AI in CPR, with emphasis on rhythm interpretation, performance optimization, and post-resuscitation care. Current evidence indicates that AI-based systems, including machine learning models for predicting shockable rhythms and real-time feedback mechanisms, may enhance critical components of resuscitation such as compression depth, rate, and recoil, thereby contributing to improved survival and neurological outcomes.^{43,44} For instance, predictive algorithms have achieved diagnostic accuracy with areas under the receiver operating characteristic curve of up to 0.87 for shockable rhythm detection during ongoing chest compressions.⁴⁴ Similarly, AI-integrated automated external defibrillators and wearable monitoring devices can facilitate earlier recognition of cardiac arrest and support individualized interventions, addressing limitations such as rescuer variability and delayed response.^{10,13}

Despite these advances, the evidence base remains inconsistent. While some studies report significant improvements in CPR quality metrics with AI-driven feedback, others demonstrate limited applicability in clinical practice. Robotic devices incorporating AI algorithms, for example, have shown hemodynamic outcomes comparable to mechanical compression systems in preclinical models, yet survival advantages remain unproven in randomized clinical trials.^{19,45} Furthermore, AI-based rhythm analysis is prone to false positives, whereby non-shockable rhythms are erroneously classified as shockable. Such errors may lead to inappropriate defibrillation attempts, delaying effective chest compressions and potentially causing harm.⁴⁶ This limitation is further compounded by the risk of clinician over reliance on algorithmic outputs, a phenomenon known as automation bias, which may impair critical judgment, reduce situational awareness, and ultimately compromise patient safety in high stakes resuscitation settings.⁴⁷ Furthermore, an umbrella review of systematic analyses comparing mechanical and manual CPR, including studies incorporating adaptive AI, reported heterogeneous outcomes. While certain subgroups demonstrated benefit with mechanical methods in prolonged resuscitation exceeding 45 minutes, other analyses indicated no advantage or even worse neurological recovery.⁴⁸ This

challenge is compounded by automation bias, in which clinicians may over-rely on algorithmic outputs, thereby compromising situational awareness and critical judgment in high-stakes scenarios.^{46,47}

Conflicting findings are also evident in VR-based platforms with AI feedback, which have improved skill retention and confidence in specific domains such as compression rate, yet instructor-led approaches occasionally outperform AI in achieving adequate compression depth and fraction.⁴⁹ This inconsistency may stem from the limited ability of current AI systems to provide nuanced, context-specific feedback comparable to experienced instructors, particularly in dynamic scenarios requiring precise depth adjustments.⁴⁶ In addition, telemedicine applications that employ AI guidance during CPR have demonstrated reduced mortality in observational studies, but randomized trials have not consistently shown reductions in no-flow time during simulations.⁵⁰ Such discrepancies are likely due to variations in study design, including differences in operator experience, device availability, and the uncontrolled nature of real-world emergencies compared with simulated settings, as seen in trials evaluating AI-assisted dispatcher performance.^{46,47} Overall, these discrepancies highlight the need for standardized protocols, large-scale datasets, and methodological rigor to reconcile divergent results and reduce bias arising from limited or non-representative training data.⁵¹

Limitations

Much of the current evidence derives from simulation-based or retrospective studies, which limits generalizability to dynamic clinical settings. Prospective, multicenter randomized controlled trials remain limited. The unpredictable nature of cardiac arrest, including environmental noise and patient heterogeneity, poses challenges to the reliability of AI systems.^{22,34} Ethical and legal considerations further complicate implementation, particularly regarding accountability for adverse outcomes influenced by AI recommendations and adherence to emerging regulations such as the European Union AI Act, which mandates transparency, human oversight, and structured risk assessment for high-risk applications.^{30,44}

Data privacy is another critical concern, particularly when multimodal inputs, including biometric signals and emergency audio, are utilized. Privacy-preserving techniques, such as federated learning, offer potential solutions by enabling algorithm development without centralizing raw patient data. Interoperability also remains a key barrier, as AI systems must seamlessly integrate with existing infrastructure, including electronic health records, defibrillators, and emergency medical services. Standards such as HL7 FHIR and ISO/IEEE 11073 facilitate real-time data exchange and structured communication, although variations in digital readiness across regions may exacerbate inequities.^{41,44} Clinician and nurse acceptance and preparedness are essential; brief exposure to AI systems can enhance operational efficiency, yet trust-building requires presenting AI as an adjunct rather than a replacement for clinical judgment.^{21,47} Interdisciplinary training programs incorporating virtual and augmented reality further support adaptability and strengthen competence among healthcare teams.²⁵

Future Research Directions

Future research should prioritize the rigorous validation of AI-based tools through prospective, multicenter randomized controlled trials encompassing diverse patient populations. The development of algorithms that explicitly address demographic and clinical biases is essential to ensure equitable performance across varied settings. Establishing collaborative policy frameworks involving clinicians, developers, and regulatory authorities will be critical for safe, standardized implementation. Focusing on these priorities is fundamental for translating AI in CPR from experimental innovation to routine clinical practice, ultimately reducing cardiac arrest mortality and enhancing long-term neurological outcomes.

Conclusion

AI holds considerable promise for advancing CPR by providing real-time feedback, optimizing compression quality, and enabling more accurate prognostic assessment. These applications have the potential to address key challenges in cardiac arrest management, including variability in resuscitation performance and limitations of conventional predictive tools. However, several barriers remain, including the need for large-scale, real-world validation, concerns regarding data privacy and system interoperability, and unresolved ethical and regulatory issues. Effective integration will require structured training for healthcare providers and sustained interdisciplinary collaboration among clinical, technological, and policy stakeholders.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors declare that they have no competing interests.

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