Review

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Role of artificial intelligence in predicting neurological outcomes in postcardiac resuscitation

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Abstract

Being an extremely high mortality rate condition, cardiac arrest cases have rightfully been evaluated via various studies and scoring factors for effective resuscitative practices and neurological outcomes postresuscitation. This narrative review aims to explore the role of artificial intelligence (AI) in predicting neurological outcomes postcardiac resuscitation. The methodology involved a detailed review of all relevant recent studies of AI, different machine learning algorithms, prediction tools, and assessing their benefit in predicting neurological outcomes in postcardiac resuscitation cases as compared to more traditional prognostic scoring systems and tools. Previously, outcome determining clinical, blood, and radiological factors were prone to other influencing factors like limited accuracy and time constraints. Studies conducted also emphasized that to predict poor neurological outcomes, a more multimodal approach helped adjust for confounding factors, interpret diverse datasets, and provide a reliable prognosis, which only demonstrates the need for AI to help overcome challenges faced. Advanced machine learning algorithms like artificial neural networks (ANN) using supervised learning by AI have improved the accuracy of prognostic models outperforming conventional models. Several real-world cases of effective AI-powered algorithm models have been cited here. Studies comparing machine learning tools like XGBoost, AI Watson, hyperspectral imaging, ChatGPT-4, and AI-based gradient boosting have noted their beneficial uses. AI could help reduce workload, healthcare costs, and help personalize care, process vast genetic and lifestyle data and help reduce side effects from treatments. Limitations of AI have been covered extensively in this article, including data quality, bias, privacy issues, and transparency. Our objectives should be to use more diverse data sources, use interpretable data output giving process explanation, validation method, and implement policies to safeguard patient data. Despite the limitations, the advancements already made by AI and its potential in predicting neurological outcomes in postcardiac resuscitation cases has been quite promising and boosts a continually improving system, albeit requiring close human supervision with training and improving models, with plans to educate clinicians, the public and sharing collected data.

Keywords: artificial intelligence, machine learning, neurological outcomes, postcardiac resuscitation

Introduction

Cardiac arrest has an extremely high mortality rate, with only one in 10 patients surviving hospital stay[1]. Numerous studies have been conducted over different time periods to determine the optimal techniques for performing resuscitation. These studies established the compression depth and rates still in use today, which are associated with survival rates and neurological outcomes[2]. Many other factors also contribute to improving the neurological outcomes of cardiac arrest, including therapeutic hypothermia (TH), ensuring proper ventilation to avoid low oxygen levels, excess oxygen, and carbon dioxide imbalances, avoiding hypotension, prompt coronary intervention when needed, and postponing neurological prognosis, as immediate evaluations can be misleading due to temporary effects of the arrest or initial treatments[3]. Several scoring systems have been developed to predict survival or neurological recovery after in-hospital and out-of-hospital cardiac arrest[4–7]. The use of these scoring systems is often challenging, as patients are frequently sedated or

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intubated, making clinical evaluation difficult and highlighting the need for artificial intelligence (AI)[8]. Neurological data is complex and requires the interpretation of a diverse set of data, including imaging scans, genetic information, electro physiological recordings, and clinical assessments, as there is sig nificant individual variability in brain function and response to treatment. The study conducted by Sandroni *et al.*[9] emphasized that a single prognostic index was insufficient to predict poor neurological outcomes, and a multimodal approach can adjust for confounders, interpret diverse datasets, and deliver a reliable prognosis. This demonstrates the need of AI to overcome the current challenges faced in the field.

Artificial intelligence has significantly transformed the healthcare sector over the years [refer to Table 1 for AI types]. AI has proven its usefulness in maintaining medical records, collecting data, and interpreting EMG[10]. The combination of artificial intelligence and machine learning has shown its value in improving patient outcomes. For example, a recent study on a machine learning-based early warning system, TREWS, for sepsis has demonstrated reduced mortality[11]. Research by Huang *et al.*[12] highlighted that explainable AI (XAI) was more effective in validating ovar ian cancer biomarkers compared to conventional methods. One of the benefits of AI in patients experiencing out-of-hospital car diac arrest (OHCA) is its ability to assist emergency physicians in making swift decisions and guiding subsequent care[13]. Predicting mortality and neurological outcomes can significantly enhance patient management and enable timely counseling for the patients' families.

In this article, we provide a concise review of the relevant scientific literature on artificial intelligence (AI), including machine learning (ML), deep learning (DL), and natural language processing (NLP), used to predict neurological outcomes after cardiac arrest. We will also explore how these models, including gradient boosting classifier (GBC), logistic regression (LR), multilayer perceptron (MLP), and random forest (RF) models, outperform conventional statistical methods[8,14], their effectiveness and limitations, and their potential to enhance patient management and safety [refer Table 2] [refer Table 3 for AI branches and Table 4 for key articles].

Discussion

Current methods of predicting neurological outcomes

Traditional methods to predict neurological outcomes of post-cardiac resuscitation patients include techniques such as clinical assessment through neurological examinations, scoring systems, blood biomarkers, electrophysiological methods, and radiological imaging using CT scan and MRI[37].

Clinical neurological assessments help in determining the prognostic status of postcardiac resuscitation patients. Key findings like absence of pupillary response, corneal reflex, poor motor response, and presence of myoclonus may serve as a foundation to determine prognostic status, however, these assessments are influenced by sedation, metabolic disturbances, hypothermia, and neuromuscular blocking agents[5,37–39].

Cardiac arrest hospital prognosis (CAHP), out-of-hospital cardiac arrest (OHCA), and cerebral performance categories (CPC) are some of the various scoring systems employed for assessment of neurological outcomes in postcardiac resuscitation patients[7]. Although these scoring systems demonstrate good

HIGHLIGHTS

- Introduction
  Cardiac arrest has a high mortality rate, with only 10% of patients surviving hospitalization.
  Traditional methods for predicting neurological outcomes postresuscitation include clinical assessments, scoring systems, blood biomarkers, and radiological imaging.
  AI has the potential to significantly enhance the accuracy and efficiency of these prognostic methods.
- Traditional methods of prediction
  Clinical neurological assessments, while valuable, are often influenced by factors such as sedation and metabolic disturbances.
  Scoring systems like CAHP and OHCA provide valuable prognostic information but have limited accuracy.
  Imaging techniques like CT scans and MRI play a crucial role but require optimal timing and are part of a multimodal approach.
  Blood biomarkers like NSE and S100B are useful but influenced by the timing of measurement.
  Electrophysiological methods such as EEG and SSEPs are associated with poor outcomes but have limitations.
- AI techniques in predicting neurological outcomes
  AI, particularly artificial neural networks (ANN), outperforms traditional methods in predicting long-term neurological outcomes postcardiac arrest.
  ANNs use continuous and categorical variables to predict outcomes with high accuracy.
  Studies have shown ANN models achieving strong validation performance (AUC of 0.906), indicating their effectiveness in clinical settings.
- Applications and case studies
  AI models have successfully analyzed EEG and MRI data to predict neurological outcomes with high precision.
  Real-world applications include using AI to predict outcomes using CT images and deep learning models analyzing MRI scans, demonstrating improved predictive accuracy.
  AI models combining EEG data and demographic information have shown high accuracy in predicting coma recovery likelihood.
- Evaluation of AI models
  Machine learning tools like XGBoost and ChatGPT-4 have demonstrated superior predictive performance compared to traditional scoring methods.
  AI models provide reliable prognostic information, aiding in resource optimization, and informed decision-making for families.
  Despite the success, AI models require close human supervision and continuous improvement.
- Challenges and limitations
  AI models face issues such as data quality, bias, transparency, and privacy concerns.
  Educating clinicians and the public about AI's strengths and weaknesses is crucial for building trust.
  Public data sources and transparent data sharing are recommended to mitigate privacy issues and biases.
- Future directions
  Advancements in machine learning and deep learning,

performance and provide valuable prognostic information, the accuracy remains limited[40].

Although radiological imaging techniques like computed tomography (CT scan) and MRI play a crucial role in detecting structural abnormalities and ischemic changes, their optimal timing is critical[41]. CT scan and MRI are often employed as a part of multimodal approach involving other methods like neurological assessments, biomarkers, and electrophysiological methods to increase prognostic accuracy[37].

Blood biomarkers such as neuron specific enolase (NSE) and S100 calcium binding protein B (S100B) have assisted to determine neurological outcomes after cardiac resuscitation in recent years[42]. These biomarkers are elevated in response to brain injury, but the accuracy is influenced by timing after the return of spontaneous circulation[37,42]. These techniques are often used as adjuncts to neurological assessments and radiological imaging[37].

Commonly employed electrophysiological methods for determining neurological outcomes include electroencephalography (EEG), somatosensory evoked potentials (SSEPs) etc.[37]. Specific EEG patterns and the absence of SSEPs is often found to be associated with poor outcomes[43,44].

Advanced machine learning techniques enhance prognostic models for neurological outcomes in cardiac arrest patients

It has been demonstrated that models utilizing a combination of biomarkers, such as neuron-specific enolase (NSE), and artificial intelligence are promising in predicting long-term neurological outcomes in comatose patients after cardiac arrest. In a recent study titled ‘Artificial Neural Network in Neurological Outcome in Cardiac Arrest’ by Szu-Yi Chou, evidence revealed that a supervised machine learning algorithm, specifically artificial neural networks (ANN), outperformed logistic regression in predicting long-term neurological outcomes, including survival, based on information available at hospital admission[15]. This suggests that integrating advanced machine learning techniques with clinical data can significantly enhance the accuracy of prognostic models.

The ANN models were developed using STATISTICA (TIBCO Software Inc.). These models employed a multilayer perceptron architecture consisting of an input layer, one hidden layer, and an output layer. The input variables included continuous factors such as age, prearrest cerebral performance category score, resuscitation duration, and mean arterial pressure (MAP) at the return of spontaneous circulation.

Categorical variables encompassed initial arrest rhythm, arrest location (categorized into out-of-hospital cardiac arrest (OHCA), telemetry unit, ICU, and nonmonitored unit), and conditions like renal or hepatic insufficiency, sepsis, and malignancy. The number of neurons in the hidden layer was empirically determined, ranging from 1 to 50[16].

This collection of clinical variables provides timely information on patient prognosis, helping to classify patients based on their suitability for clinical interventions. This approach prevents the overexposure to treatments that would not be beneficial in the long-term, redirecting timely management only to those who require it and whose prognosis would change significantly.

particularly in imaging techniques like fMRI and DTI, offer promising future applications.
Collaboration between AI experts, clinicians, and researchers is essential for developing effective AI-driven tools.
Emerging AI applications, such as AI Watson for Oncology and Google’s deep learning algorithm for diabetic retinopathy, highlight the potential for AI to transform healthcare practices globally.

AI-driven models demonstrate high accuracy in predicting neurological outcomes for cardiac arrest patients

A study published by F Jiang in ‘Artificial Intelligence in HealthCare’ revealed that the main predictors of favorable neurological outcomes include cardiopulmonary resuscitation duration, initial cardiac arrest rhythm, arrest location, metastatic or hematologic malignant disease, pneumonia, and respiratory insufficiency. Based on these parameters, the developed artificial neural network model for in-hospital cardiac arrest patients treated with targeted temperature management (TTM) demonstrated strong validation performance, achieving an area under the curve (AUC) of 0.906. This is significant because the AUC measures the model’s ability to differentiate between classes.

The relatively high AUC values indicate that the model can effectively distinguish between favorable and unfavorable neurological outcomes in-hospital cardiac arrest patients[17]. The robustness of this model suggests that it could be adapted for use in various clinical settings, further enhancing its utility in medical practice.

Using AI in this artificial neural network (ANN) model, which employs supervised learning, replicates biological neural networks to identify relevant predictive markers in diagnostics, explore nonlinear data relationships, enhance data interpretation, and design more efficient diagnostic and predictive methods, thereby outperforming conventional statistical approaches[18,19,45,46].

Table 1

Artificial intelligence.

Capabilities based:		
Artificial narrow intelligence	Performs a set of predetermined function	
Artificial general intelligence		
Artificial super intelligence		
Functionality based:		
Reactive machines AI	Present solely on present data, can perform a narrowed range of predefined tasks	For example, IBM Chess Program
Limited memory AI	Make informed and improved decisions by studying the past data from its memory	For example, Self-driving cars
Theory of mind AI	Focus mainly on emotional intelligence so that human believes and thoughts can be better comprehended	Not yet fully developed
Self-aware AI	Have their own consciousness and become self-aware	Hypothetical

Table 2

Summary.

Objective	Role of AI in predicting neurological outcomes in postcardiac resuscitation
Methodology	Detailed narrative review of all recent studies of AI, ML algorithms, prediction tools, and assess their benefit regarding our objective as compared to traditional methods
Traditional methods	Clinical assessment like neurological examination (pupillary response, corneal reflex, and motor response), scoring systems (CAHP, OHCA, and CPC), blood biomarkers (NSE), electrophysiological methods (EEG), and radiological imaging (CT scan/MRI)
Use of AI	Advanced ML techniques and use of ANN improve accuracy of prognostic models when integrated with clinical data, enhance data interpretation, identify relevant predictive markers in diagnostics and design more efficient diagnostic/predictive methods. ML algorithms to analyze EEG and deep learning models to analyze MRI images improve accuracy of possible outcome and improve early diagnosis respectively as noted successfully on some studies. Helps resource optimization by early recognition of hypoxic brain injury. AI can help personalize healthcare and possibly help families make informed decisions based on reliable prognostic information
Limitations	Bias in population groups with different ethnic and socioeconomic backgrounds, lack of transparency and explainability, healthcare data security, accuracy and reliability
Future directions/goals	Digital imaging is becoming more vital. Improvement in fMRI and DTI enable noninvasive methods of brain visualization. Use of ChatGPT-4 functioned well in death and severe neurological prognosis. XGR had the best prediction accuracy compared to SVM and LR. CT scan models which can detect lung cancer with accuracy comparable or better than six radiologists.
	Ethical concerns and limitations should be addressed. Close human monitoring, ensuring proper data security, uses diverse population groups to reduce bias, have AI models explain clearly its process and rationale to improve transparency should all be integral goals to aim for moving forwards
Conclusion	Despite limitations, many advancements have been made by AI and its potential in our objective which appears promising. As the system continues to improve, it does need close human supervision, education, sharing collected data and aim to continually improve whilst manage limitations
Abbreviations	AI, artificial intelligence; ANN, artificial neural networks; CAHP, cardiac arrest hospital prognosis; CPC, cerebral performance categories; CT, computed tomography; DTI, diffusion tensor imaging; EEG, electroencephalogram; fMRI, functional MRI; LR, logistic regression; ML, machine learning; OHCA, out-of-hospital cardiac arrest; NSE, neuron specific enolase; SVM, support vector machine; XGR, extreme gradient boosting

Another impressive achievement was reported by Tjepkema-Cloostermans, who achieved a positive predictive value of up to 100%. They developed a predictive model that can be used at the bedside with electroencephalogram patterns[20,21]. Established electroencephalogram patterns within an artificial intelligence algorithm, along with the other mentioned parameters, could aid in discerning clinical decisions regarding the treatment of patients.

Applications and case studies

The use of artificial intelligence (AI) in predicting neurological outcomes after cardiac resuscitation has shown significant potential to enhance clinical decision-making. Predictive models leverage patient data by integrating clinical records, imaging data, and physiological signals to provide comprehensive assessments of patient status and recovery trajectories. Clinical data includes patient demographics, medical history, and details of the cardiac event and resuscitation efforts. Imaging data, such as MRI or CT scans, offer insights into brain structure and potential damage, while physiological signals, like EEG and heart rate variability, provide real-time information on brain activity and overall patient stability[22,23].

One notable example is the use of machine learning algorithms to analyze EEG data for predicting neurological outcomes. Studies have shown that these algorithms can identify patterns associated with poor or favorable outcomes with greater accuracy than traditional clinical assessments. For instance, deep learning models have been utilized to extract features from EEG signals, such as background continuity and periodic elements, to predict patient recovery with high precision[22,44].

Another significant advancement is the use of deep learning models to analyze MRI images. These algorithms can detect subtle changes and abnormalities that may not be visible to the human eye, improving early prognosis[7,23].

Real-world case studies

The practical application of AI in clinical settings has yielded several success stories. Kawai *et al.* implemented an AI-based model using CT images to predict neurological outcomes 3 h postresuscitation showing better performance than traditional methods in terms of precision-recall, highlighting the potential of AI in early and accurate outcome predictions[47]. Another notable case involves a multicenter study where deep learning models were used to predict outcomes based on MRI scans, reporting significant improvements in predictive accuracy. This has enhanced patient management and provided valuable data for ongoing research and development[7,23].

Additionally, a study by Zheng *et al.* developed a multiscale deep neural network to analyze EEG data and demographic information for predicting coma recovery likelihood. This model demonstrated high accuracy and improved performance with longer EEG duration, showcasing AI's potential to enhance prognostication in clinical settings[48].

In another study, Krones *et al.* used a deep learning algorithm to analyze EEG recordings from postcardiac arrest patients to predict neurological outcomes. The algorithm demonstrated higher predictive accuracy compared to traditional scoring systems[49]. Similarly, several studies have successfully employed advanced AI techniques to integrate MRI and clinical data for predicting long-term outcomes. For instance, Hatami *et al.*[34] utilized a convolutional neural network – long short-term mem ory (CNN-LSTM)-based multimodal MRI and clinical data fusion approach to predict functional outcomes in stroke patients, demonstrating the effectiveness of combining different

Table 3

Branches of AI.

Machine learning	Science of getting machines to interpret, process and analyze data in order to solve real-world problems. Types – supervised, unsupervised, and reinforcement learning
Deep learning	Process of implementing Neural Networks on high dimensional data to gain insights and form solutions. For example, face verification algorithm on Facebook, self-driving cars, virtual assistants like Siri, Alexa
Natural language processing (NLP)	The science of drawing insights from natural human language in order to communicate with machines and grow businesses. For example, Twitter uses NLP to filter out terroristic language in their tweets, Amazon uses NLP to understand customer reviews and improve user experience
Robotics	Branch of artificial intelligence which focuses on different branches and application of robots. For example, Sophia the humanoid is a good example of AI in robotics
Expert systems	An AI-based computer system that learns and reciprocates the decision-making ability of a human expert. Eg. mainly used in information management, medical facilities, loan analysis, and virus detection
Fuzzy logic	A computing approach based on the principles of 'degrees of truth' instead of the usual modern computer logic, that is Boolean in nature. For example, used in the medical fields to solve complex problems involving decision-making, used in automatic gearboxes, vehicle environment control

modalities through deep learning. Another study by Wei *et al.*[35] focused on predicting long-term outcomes for acute ischemic stroke using multimodel MRI radiomics and clinical variables, highlighting the potential for AI to improve prognostic accuracy. Both studies showcased the potential of advanced AI techniques in enhancing prognostication in clinical settings.

These implementations underscore AI's transformative potential in healthcare. Success stories illustrate how AI can complement traditional methods, offering more precise and reliable predictions. However, integrating AI into medical practice comes with challenges, including data quality issues, algorithm transparency, and the need for continuous validation in diverse patient populations[7,22,23]. Addressing these challenges and continuously refining AI models can lead to more personalized and accurate prognostic tools, ultimately improving patient outcomes and resource allocation in critical care settings.

Evaluation of AI models

Mayampurath *et al.*[8] compared five different machine learning tools. The extreme gradient boosting tool (XGBoost) was found to be superior to traditional scoring methods, XGBoost model had a sensitivity of 72%, specificity of 74%, a positive predictive value of 90%, and a negative predictive value of 45% for distinguishing individuals with favorable neurological outcomes.

The prediction of mortality came similar between the two, making the sensitivity and specificity of 63 and 91%, respectively. However, AI was more likely to predict poor neurological outcome, resulting in an 88% sensitivity and 49% specificity[25,47,50,51] [refer Table 5].

This phenomenon was called hallucinations of ChatGPT-4, defined as a type of irrational responses to the input given in a context[25].

Accurate prediction of neurological outcome is crucial for tailoring treatment plans[52]. Early recognition of hypoxic brain injury risk is important to resource optimization[26]. Reliable prognostic information helps families make informed decisions[25]. Multiple studies overestimated the superiority of AI over experts[27]. Despite the astonishing AI performance, it is best to keep close human supervision, keep training and improving models[25,28].

Challenges and limitations

AI models face several challenges, including bias, transparency, privacy issues, and liability in clinical settings[27–29], and addressing them is important to ensure its effective and ethical use in clinical practice. Educating clinicians and the public on AI's strengths and weaknesses can enhance trust. The author recommended collecting data from a public source to limit privacy issues[29]. To improve transparency and reduce risks, Daneshjou *et al.*[30] recommended sharing data or providing detailed descriptions of the data used to train AI models.

Bias in the AI algorithm is one of the primary ethical concerns, an AI model trained predominantly on data from a specific demographic group, may not generalize well to other groups, such as those from different ethnic backgrounds or with different socioeconomic statuses[27]. To mitigate bias is to ensure that the training data is diverse and representative of the entire patient population involving the collection and incorporation of data from various demographic groups and clinical settings. Implementing fairness-aware machine learning techniques can help identify and correct biases during the model development process[27].

Among clinicians and patients, transparency and explainability are critical for gaining trust and acceptance. AI models, particularly those based on deep learning, can often function as 'black boxes', making it challenging to understand how they arrive at their predictions. This lack of transparency can hinder the adoption of AI in clinical practice, as clinicians may be reluctant to rely on models they do not fully understand[28]. Developing AI models that provide interpretable and explainable outputs may enhance transparency. Techniques such as Explainable AI (XAI) can help demystify AI models by offering insights into how the models make decisions. Detailed documentation of the AI model's development, including the data sources, preprocessing steps, and validation methods, can also improve transparency[28,29].

Using sensitive patient data in the AI models raises a concern of privacy and data security. Healthcare information management (HIM) professionals must safeguard patient data through security measures, privacy policies, and staff training. They develop and implement organizational policies concerning privacy and ensure compliance, challenging current practices as necessary[28]. Privacy insurance should be integrated into areas of concern[52]. Stanfill and Marc[31] emphasized testing cur rent privacy laws and regulations to explore their applicability in AI development.

AI models require continuous validation and improvement to maintain their accuracy and reliability. Establishing a framework

Table 4

Summary of key articles.

Author	Key point
Johnsson *et al.*[15]	A supervised ML model using ANN predicted neurological recovery and survival excellently, outperforming a conventional model based on logistic regression with prehospital setting carrying most details amongst data at time of hospitalization
Chou *et al.*[16]	The generated ANN-boosted, CASPRI-based model exhibited good performance for predicting TTM neurological outcome, suggesting its clinical application to improve outcome prediction, facilitate decision-making, and formulate individualized therapeutic plans for patients receiving TTM
Chung *et al.*[17]	The ANN models achieved highly accurate and reliable performance for predicting the neurological outcomes of successfully resuscitated patients with IHCA, which can assist with decision-making and optimal postresuscitation strategies
Jiang *et al.*[18]	IBM Watson system includes both ML and NLP modules as is required of a successful AI system. Current regulations lack standards to assess the safety and efficacy of AI systems. AI systems need to be trained (continuously) by data from clinical studies. To provide incentives for sharing data on the system
Chung *et al.*[19]	The ANN-based models achieved reliable performance to predict MNI and 3-month outcomes after thrombolysis for AIS to help assist in decision-making, especially when invasive adjuvant strategies are considered
Tjepkema-Cloostermans *et al.*[20]	Deep learning of EEG signals outperforms any previously reported outcome predictor of coma after cardiac arrest, including visual EEG assessment by trained EEG experts
Viderman *et al.*[21]	AI might be useful in predicting cardiac arrest, heart rhythm disorders, and postcardiac arrest outcomes, as well as in the delivery of drone-delivered defibrillators and notification of dispatchers
Zubler Tzovara[22]	Existing studies show overall high performance in predicting outcome, relying either on spontaneous or on auditory evoked EEG signals
Andersson *et al.*[23]	ANNs provided good to excellent prognostic accuracy in predicting neurological outcome in comatose patients post OHCA. The models which included NSE after 72 h and NFL on all days showed promising prognostic performance
Amacher *et al.*[7]	Two postarrest scores (OHCA and CAHP) showed good prognostic accuracy for predicting neurological outcome after cardiac arrest and may support early discussions about goals-of-care and therapeutic planning on the ICU. A prearrest score (GO-FAR) showed acceptable prognostic accuracy and may support code status discussions
Mayampurath *et al.*[8]	The gradient boosted machine algorithm was the most accurate for predicting favorable neurologic outcomes in IHCA survivors
Aqel *et al.*[24]	The application of AI in prehospital emergency care has shown promise in detecting shockable rhythms, predicting resuscitation success, and enhancing CPR quality through real-time feedback. AI's potential extends to predicting neurological outcomes after resuscitation and even addressing cardio-oncology cardiac arrests, improving risk prediction and resource allocation. Limitations - the need for large, annotated datasets, scarce quality-controlled rhythm annotations, regulatory challenges, and vulnerability to adversarial attacks. Future studies are needed to address data quality and biases, advance the interpretability of AI models, and ensure robust security measures
Amacher *et al.*[25]	ChatGPT-4 showed a similar performance in predicting mortality and poor neurological outcome compared to validated postcardiac arrest scores. However, more research is needed regarding illogical answers for potential incorporation of an LLM in the multimodal outcome prognostication after cardiac arrest
Kawai *et al.*[26]	A ML model using head CT images with transfer learning was used to predict the neurological outcomes at 1 month. It had superior accuracy to conventional methods and could help optimize treatment
Nagendran *et al.*[27]	Most nonrandomised trials are not prospective, are at high risk of bias, and deviate from existing reporting standards. Data and code availability are lacking in most studies, and human comparator groups are often small. Future studies should diminish risk of bias, enhance real-world clinical relevance, improve reporting and transparency, and appropriately temper conclusions
Liyanage *et al.*[28]	We need to ensure meticulous design and evaluation of AI applications. The primary care informatics community needs to be proactive and to guide the ethical and rigorous development of AI applications so that they will be safe and effective
Reddy *et al.*[29]	Concerns include the possibility of biases, lack of transparency with certain AI algorithms, privacy concerns with the data used for training AI models, and safety and liability issues with AI application in clinical environments which need to be addressed
Daneshjou *et al.*[30]	Three issues in datasets that are used to develop and test clinical AI algorithms for skin disease include sparsity of data set characterization and lack of transparency, nonstandard and unverified disease labels, and inability to fully assess patient diversity used for algorithm development and testing
Stanfill and Marc[31]	HIM professionals are in a unique position to take on emerging roles with their depth of knowledge on the sources and origins of healthcare data. The challenge is to identify leading practices for the management of healthcare data and information in an AI-enabled world
Kagiyama *et al.*[32]	The capability of AI to analyze unstructured data expands the field of cardiovascular research. In addition, AI will further increase its contribution to mobile health, computational modeling, and synthetic data generation, with new regularizations for its legal and ethical issues
Bahrami and Forouzanfar[33]	The proposed deep learning approach was successful in forecasting the occurrence of sleep apnea from single-lead ECG. It can therefore be adopted in wearable sleep monitors for the management of sleep apnea
Hatami *et al.*[34]	CNN-LSTM based ensemble mode offers an original way to automatically encode the spatio-temporal context of MR images in a deep learning architecture surpassing baseline
Wei *et al.*[35]	Radiomics features extracted from DWI and ADC images can serve as valuable biomarkers for predicting poor clinical outcomes in patients with AIS. Furthermore, when these radiomics features were combined with multiclinical features, the predictive performance was enhanced. The prediction model has the potential to provide guidance for tailoring rehabilitation therapies based on individual patient risks for poor outcomes
Liu *et al.*[36]	In China, most of the treatment recommendations of WFO are consistent with the recommendations of the expert group and can improve efficiency, although a relatively high proportion of cases are still not supported by WFO and it needs to learn regional characteristics to improve assistive ability. Therefore, WFO cannot currently replace oncologists

ADC, apparent diffusion coefficient; AIS, acute ischemic stroke; ANN, artificial neural network; CAHP, cardiac arrest hospital prognosis; CASPRI, cardiac arrest survival postresuscitation in-hospital; CNN-LSTM, convolutional neural network, long short-term memory; DWI, diffusion-weighted imaging; EEG, electroencephalogram; GO-FAR, good outcome following attempted resuscitation; HIM, health information management professionals; IHCA, in-hospital cardiac arrest; ML, machine learning; MNI, major neurologic improvement; NFL, neurofilament light; NSE, neuron-specific enolase; OHCA, out-of-hospital cardiac arrest; TTM, targeted temperature management; WFO, Watson for oncology.

Table 5

Comparison between AI and traditional prognostic measures for PNO.

	ChatGPT-4		Traditional prognostic measures for PNO		
	In-hospital mortality	Poor neurological outcome	OHCA score	PROLOGUE score	CAHP score
Mortality at hospital discharge was	43% (95% CI: 40–47%; $n=309$)	–			
Mean predicted mortality	44% (95% CI: 42–46%)	–			
Mean AUROC	0.85		0.83		
Prevalence %, (95% CI)	43.3 (39.7–47.1)	54.3 (50.5–58.0)			
Sensitivity %, (95% CI)	62.8 (57.1–68.2)	87.9 (84.2–90.9)	95% (89–97)	72.4 (67.5–76.9)	88 (85.2–91.6)
Specificity %, (95% CI)	91.3 (88.2–93.9)	49.1 (43.5–54.6)	53% (40–67)	72.4 (67.5–76.9)	83 (76.1–88.4)
Positive likelihood ratio, (95% CI)	7.25 (5.2–10.1)	1.73 (1.5–1.9)	86% (80–91)		
Negative likelihood ratio, (95% CI)	0.41 (0.4–0.5)	0.25 (0.2–0.3)	76% (59–88)		
Odds ratio, (95% CI)	17.79 (11.7–26.9)	6.97 (4.8–10.1)			
Positive predictive value %, (95% CI)	84.7 (79.4–89.1)	67.2 (62.9–71.3)		77.3 (72.5–81.6)	93 (90–95.4)
Negative predictive value %, (95% CI)	76.2 (72.2–80.0)	77.3 (71.0–82.8)		70.6 (65.5–75.4)	74 (66.9–80.3)

for continuous monitoring and validation of AI models can help ensure their ongoing effectiveness. Collaborating with clinicians to gather real-world feedback and incorporating it into model updates can further enhance the models' performance and applicability[31].

Future directions

Over the years, we have witnessed the emergence of novel innovations as well as the emergence of artificial intelligence (AI) and machine learning (ML). ML, a subtype of AI enables a system to acquire information and utilizes the use of algorithms that take in data, recognize specific patterns, and then apply the acquired model to make assessments and forecast outcomes[32]. Neural networks in deep learning, a subset of machine learning, can be used for a variety of tasks, including language recognition, natural language interpreting, and neuroimaging-based disease diagnosis[53]. Random forests (RF) is generally used in the pre diction of disease progression[54] and support vector machines (SVM) is used in the classification of diseases[55].

Significant improvements in artificial intelligence performance for medical image analysis have been made achievable by the use of a particular type of deep neural network called a convolutional neural network (CNN)[56,57]. For instance, after being examined on 70 sleep recordings, an inventive deep learning framework based on a combined CNN-LSTM model predicted the probability of sleep apnea from a single-lead ECG with an accuracy rate of up to 94.95%[33]. Digital imaging is becoming more and more vital for neurological and oncologic disorders. Thus, improvements in functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI) enable noninvasive methods of brain visualization[58]. A new imaging technique for use in healthcare, hyperspectral imaging (HSI), is used for surgical gui dance with images and the identification of disorders.

Further research depicted that when compared to established postcardiac attack scores, ChatGPT-4 functioned well in detecting death and severe neurological prognosis. As an outcome, it may prove to be an asset in the future in identifying potential risks in adult cardiovascular arrest patients[25]. The extreme gradient boosting (XGB) model displayed the best prediction accuracy of 0.87 and 0.83 as compared to support vector machine (SVM) and logistic regression (LR) in Cheng *et al.*[14] ML-based model for determining the 30-day mortality rate and survival-to-discharge rate after cardiac arrest of 1071 patients. Using CT scans, Kawai *et al.*[26] proposed an AI-based prognostic system for predicting the likelihood of neurological outcomes from a total of 321 cardiopulmonary arrest patients after three hours of resuscitation.

The collaboration of AI experts, clinicians, and researchers has helped in the development of many multidisciplinary initiatives. AI Watson for oncology has been developed to reduce doctors' workloads and help train future physicians by rapidly and precisely recommending treatments for the majority of Chinese patients with lung cancer. Additionally, it will help emerging nations with uneven medical advancement by establishing lung cancer therapy across China and promoting patient-doctor trust[36]. The research team at Google has created a deep learning algorithm that can recognize warning signs of diabetic retinopathy by analyzing retinal pictures. This may render it easier for physicians to screen more patients in places with a shortage of resources[59]. Another example shows, a CT scan model created by Google's AI jointly with scientists from Northwestern University, NYU-Langone Medical Center, and Stanford Medicine can detect lung cancer with accuracy on track with or superior to that of six radiologists[60]. Omics devices, smartphone-based electronic testing, and wearables may all accurately track an individual's lifestyle, which allows for the implementation of metabolic lifestyle disorder prevention and control measures[59]. Escalante *et al.*[61] established a noninvasive AI-based methodology for screening acute leukemia by investi gating specific features of bone marrow structure.

AI raises critical ethical issues and presents challenging barriers as it benefits the field of healthcare. The two most important ones are interoperability and data security. Numerous electronic health record, or EHR, platforms and other digital tools are used by many healthcare systems; however, they might not be compatible with the latest AI technologies or with one another. The effectiveness of AI systems may be diminished by this absence of interoperability, which may hinder the simple sharing of patient data[62]. Customized healthcare applications should be the main focus of future research. Interventions that are more individualized and efficient will be made possible by artificial intelligence's ability to evaluate tremendous amounts of genetic and lifestyle data. This approach could improve treatment outcomes and alleviate the side effects[62].

Conclusion

The objective of this article was to review and compare the different models of artificial intelligence (AI) used in predicting neurological outcomes of patients who have undergone cardiac resuscitation. These models integrate clinical data to detect favorable as well as unfavorable neurological outcomes in patients with cardiac arrest. Limitations of AI have been discussed extensively in this article, including data quality, bias, privacy, and transparency.

AI generated algorithms can identify intricate patterns and hidden structures, which has made it feasible for AI experts, clinicians, and researchers to collaborate on solutions through many multidisciplinary initiatives. This will help improve the healthcare systems of developing countries in the future, allowing medical professionals to manage situations more efficiently, save time, and reduce unnecessary healthcare costs.

AI advancements have been extensive, and its potential in determining neurological outcomes in postcardiac resuscitation cases is promising as it continues to improve. However, it is necessary to implement policies that safeguard patient confidentiality and ensure anonymity. Multiple studies have over-projected the superiority of AI over human expertise, which may not necessarily benefit the patient. Therefore, it is advisable to always promote human supervision over AI involvement and focus on improving these models in the near future.

Ethical approval

Ethical approval was not required for this review.

Consent

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Author contribution

M.M.K.: conception and design of the study, drafting the manuscript, critical revision of the article for important intellectual content, and final approval of the version to be published; H.A.A.: acquisition of data, analysis and interpretation of data, drafting sections of the manuscript, and revising it critically for important intellectual content; R.E.: acquisition of data, drafting sections of the manuscript, revising it critically for important intellectual content, and providing final approval of the version to be published; N.R.A.: assistance in data collection, drafting sections of the manuscript, and revising it critically for important intellectual content; M.B.M.A.: data interpretation, drafting sections of the manuscript, and revising it critically for important intellectual content; B.I.S.: analysis and interpretation of data, drafting sections of the manuscript, and revising it critically for important intellectual content; R.R.F.: data collection and interpretation, drafting sections of the manuscript, and revising it critically for important intellectual content; S.R.K.: assistance in data collection, drafting sections of the manuscript, and revising it critically for important intellectual content; H.F. and A.B.: analysis and interpretation of data, drafting sections of the manuscript, and revising it critically for important intellectual content; U.J., S.A., and M.S.K.: data collection, drafting sections of the manuscript, and revising it critically for important intellectual content.

Conflicts of interest disclosure

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or nonfinancial interest (such as personal or professional relationships, affiliations, knowledge, or beliefs) in the subject matter or materials discussed in this manuscript.

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