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Use of Artificial Intelligence in Early Warning Score in Critical ill Patients: Scoping Review

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Abstract
Early Warning Score (EWS) systems can identify critical patients through the application of artificial intelligence (AI). Physiological parameters like blood pressure, body temperature, heart rate, and respiration rate are encompassed in the EWS. One of AI's advantages is its capacity to recognize high-risk individuals who need emergency medical attention because they are at risk of organ failure, heart attack, or even death. The objective of this study is to review the body of research on the use of AI in EWS to accurately predict patients who will become critical. The analysis model of Arksey and O'Malley is employed in this study. Electronic databases such as ScienceDirect, Scopus, PubMed, and SpringerLink were utilized in a methodical search. Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA SR) guidelines were utilized in the creation and selection of the literature. This analysis included a total of 14 articles. This article summarizes the findings on several aspects: the usefulness of AI algorithms in EWS for critical patients, types of AI algorithm models, and the accuracy of AI in predicting the quality of life of patients in EWS. The results of this review show that the integration of AI into EWS can increase accuracy in predicting patients in critical condition, including cardiac arrest, sepsis, and ARDS events that cause inhalation until the patient dies. The AI models that are often used are machine learning and deep learning models because they are considered to perform better and achieve high accuracy. The importance of further research is to identify the application of AI with EWS in critical care patients by adding laboratory result parameters and pain scales to increase prediction accuracy to obtain optimal results.

Keywords: Early Warning Score, Artificial Intelligence, Machine Learning, Computational Intelligence, Critical Patients.

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1. INTRODUCTION

Critical patients require precise and timely care when receiving home health care. Until a patient passes away, the Early Warning Score (EWS) is a tool employed to predict their condition (Abbott et al., 2018). To predict the patient's clinical condition based on vital sign data, complex learning models must be applied in a transparent and explanatory manner to critical patient conditions (Chiew et al., 2019). Several physiological data parameters in EWS have developed, such as the National Early Warning Score (NEWS) and Modified Early Warning Score (MEWS), which have demonstrated less stable accuracy of results (Smith et al., 2008). This can cause the patient to fall into critical condition.

By using a clinical multicenter research model, it is possible to predict a patient's critical condition before they pass away, which can help delay the need for intervention until the patient is admitted to the intensive care unit (Dziadzko et al., 2018; Nielsen et al., 2022). Artificial Intelligence (AI) models provide a new discourse for predicting acute critical patients earlier with a higher degree of precision than EWS (Barton et al., 2019; Shickel et al., 2019). This is consistent with Kang's, et al., (2020) research, which demonstrates that AI algorithms outperform traditional triage tools and EWS in accurately predicting critical patient care needs using EMS information (Kang, et al., 2020).

Artificial Intelligence (AI) is a product of technological advancements that have contributed to the development of new applications in the medical and nursing fields. These applications aid medical professionals in diagnosing patients and conducting clinical follow-ups, which can enhance the quality of care for critically ill patients. Another example of AI is the Early Warning Score (EWS), which is currently being implemented into practice (Lei, 2017; Tang et al., 2021). The physiological parameters monitored in EWS indicators considered EWS systems are the patient's respiratory rate, oxygen saturation, systolic blood pressure, pulse rate, level of consciousness, and temperature (Royal College of Physicians, 2017; Royal College of Physicians, 2019). In hospital clinical practice, physicians will administer clinical interventions that result in high EWS if they notice elevated EWS values or high EWS results. The primary rationale behind utilizing AI-based EWS for forecasting the deterioration in the clinical state of critical patients is the utilization of machine learning, which decreases errors in diagnosis prediction and aids in decision-making for critical patients (Lauritsen, et al., 2020; Lee et al., 2020). The use of artificial intelligence (AI) technology in the Early Warning System (EWS) for patients with life-threatening illnesses is indicative of the technology's expanding application in Indonesia's healthcare industry. When it comes to supporting medical service providers and helping the medical team reach a final decision, technology is crucial (Romero-Brufau et al., 2021).

Several previous studies have demonstrated the advantages of implementing EWS-related AI for hospitalized critical patients. Thus, a scoping review is required to conduct a comprehensive analysis of the application of artificial intelligence (AI) in Early Warning Scores (EWS) for critical patients. The scoping review provides a thorough understanding of how EWS-related AI is applied to predict the deterioration in critical patients' clinical status, which lowers hospital mortality.

2. RESEARCH METHOD

A scoping review is a specific method that aims to ‘map the literature’ on a topic of interest to identify gaps in knowledge (Arksey & O’Malley, 2005; Armstrong et al., 2011). This approach was an appropriate approach for this review as it allowed for the inclusion of variety of studies. Design, especially when there is new information being discovered. It is distinct from a systematic review in that it does not entail evaluating the caliber of the literature. Instead, of reporting on the breadth and depth of a particular subject, these reports summarize a variety of evidence. The review was guided by the five stages identified by Arksey and O'Malley (18): (1) defining the objectives and search questions; (2) identifying relevant research; (3) selecting a study; (4) displaying data as graphs and qualitative themes; and (5) collecting data and composing a report (Arksey & O'Malley, 2005). The question for this study is "What are the comprehensive images of the application of AI related to EWS in identifying clinical changes in critical patients?"

A literature search associated with the full text of this article employs databases, including PubMed, ScienceDirect, Scopus, and SpringerLink. Boolean literature search operators "OR/AND". We utilized a range of search terms such as "early warning score" AND "artificial intelligence" OR "machine learning" OR "computational intelligence" AND "critical patients. intelligence" AND "critical patients". Additionally, we expanded our search to include government websites associated with the Department of Health and investigated graduate theses that were accessible. Examining the references listed in the studies that were included enhanced our search. We employ specific filters to improve the accuracy of our results, even though our searches are limited to the year of publication. The researcher considers each study's scope and ability to address the research questions when selecting relevant research. Publications discussing AI models for EWS in critical patients—particularly adult patients, as pediatric patients have different EWS parameters than adult patients—are encompassed if they adhere to certain inclusion criteria. Critical patients who were hospitalized participated in the reviewed articles. Reports, editorials, and non-English articles are not accepted.

Iterative steps are employed in determining which studies to include in the scoping review; team discussions are utilized to add clarity at this stage and are primarily led by the lead author. To conduct this scoping review, pertinent information about the objectives and methods of relevant publications was compiled and arranged, and the literature was independently searched through dependable databases. The obtained articles were examined for similarities and differences. Figure 1: An explanation of the PRISMA-SR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Review) guidelines' search and selection process for articles to be utilized as literature (McGowan et al., 2020).

3. RESULTS AND DISCUSSION

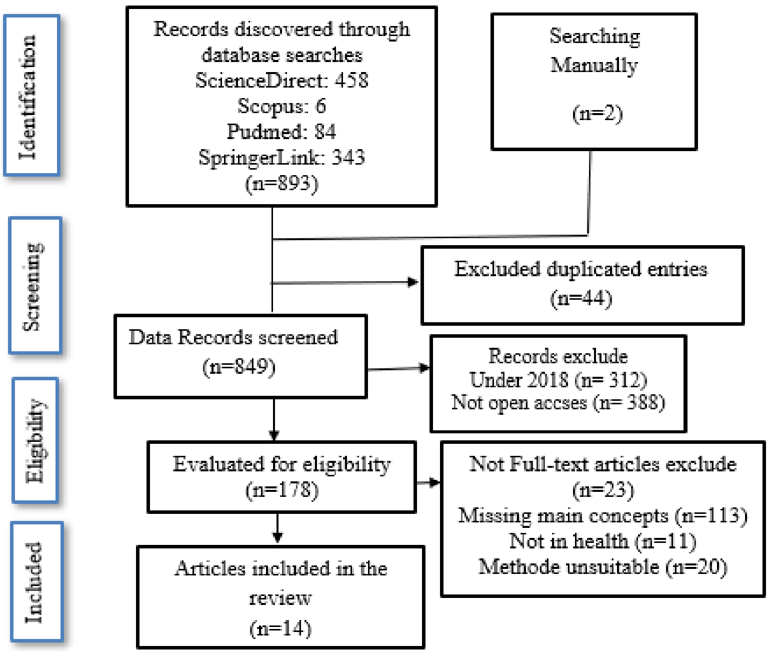

Figure 1. PRISMA SR flow diagram of studies search

The database search results of 893 articles, with details from ScienceDirek 458 articles, Scopus 6 articles, PubMed 84 articles, Springerlink 343 articles, duplicate screening of 44 articles, in accordance with the year of publication ≤ 2018 318, Not open access 388, so the remaining 178 articles are evaluated for feasibility, not full text 23 articles, missing main concept 113 pieces, unhealthy 11, unsuitable method 20 articles thus, the remaining 14 articles were reviewed. Extraction results of 14 journals were analyzed and summarized based on author, year of publication, purpose, method, setting, findings, and recommendations.

Of the selected studies, 10 performed a retrospective analysis of vital sign data, while two trials and two studies used prospective cohort study design and two productive observational studies. Only twelve studies underwent continuous analysis. One article was evaluated using the EMT, and vital sign measurements were conducted using a tool that was examined using the EWS score. By contrast, those vital signs were subjected to triage analysis in the one remaining study. These investigations were performed in medical facilities, but the study by (Spangler et al., 2019) was conducted in a prehospital setting.

Data extraction from selected literature. The articles obtained were extracted from data in the form of a matrix in Microsoft Word. The domains used in data extraction include the name of the researcher, year, purpose, method, setting, findings, recommendations, and findings, see Table 1.

Table 1. Matrix of analysis in the literature

No	Author Year, Country	Aim	Method	Findings	Recommendation
1	(Kang et al., 2020) Korea	To develop and validate related Artificial Intelligence (AI) algorithms in predicting the critical care needs of patients	The multicenter retrospective cohort study	Compared with conventional triage and EWS assessments, the Artificial Intelligence (AI) algorithm can predict the clinical status needs of critical patients with 95% accuracy utilizing EMS data.	Deep learning algorithms require model development, and the addition of a larger population than in other countries would be great.
2	(Lauritsen, et al., 2020) Denmark	To detect acute critical illnesses and more complex clinical conditions at an early stage.	CROSS-TRACKS retrospective cohort record database	Two models summarize the predictive power of xAI-EWS. The first model is the individual xAI-EWS model, which indicates an elevated probability of developing an acute critical illness. The second population-based xAI-EWS model can forecast more advanced clinical outcomes (sepsis, AKI, ALI).	Other techniques that increase the number of respondents in the database can perform its development with more varied parameters.
3	(Lee et al., 2021) South Korea	To validate DEWS in a large multicenter cohort and compare the predictive performance of IHCA DEWS with MEWS	Retrospective cohort study	MEWS 0.754 has a lower internal AUROC predictive performance than DEWS 0.860. When assessing the incidence of cardiac arrest, DEWS outperforms traditional MEWS in terms of specificity and sensitivity.	To replace other trigger scoring systems in the RS with DEWS in clinical practice, more research and carefully planned prospective clinical trials are required.

				DEWS can predict more cardiac arrest events (30 minutes to 24 hours) and reduce false alarms by nearly ½ of MEWS.	
4	(Soudan et al., 2022) United Arab Emirates	To identify the predictive model that correlates with the patient's vital signs, leading to the most precise predictions for the likelihood of cardiac arrest.	Experimentation	Several trials were conducted by employing six AI algorithms regarding the results of vital signs from 1 hour to 12 hours, the highest result being the Random Forest model more than 80%.	None
5	(Pirneskoski et al., 2020) Finlandia	To compare the accuracy of conventional NEWS prediction performance with Random Forest machine learning using vital signs the addition of glucose parameters	Retrospective registry studies such as this	Machine learning techniques generate better prediction results than EWS and traditional triage. It has been demonstrated that incorporating variables to the EWS that are not part of the TTV parameters—like blood sugar—increases the likelihood of death.	Prospective studies can be employed by future researchers, as more work is required to validate this new risk stratification model. Considering the challenges with generalizability, comparable research in various pre-hospital. Additional research could be performed particularly on diverse populations, on other variables that can be developed in machine learning.
6	(da Silva et al. 2021) Brazil	To predict clinical changes during critical conditions using the calculation of the prognostic index in the hospital utilizing the	Experiments with the deep-signs model	Experiments demonstrate that vital signs with DeepSign incorporation have been applied to predict critically ill patients (accuracy > 80%)	To conduct experiments with the DeepSign model using real data collected from ICU patients, and to compare the results of the DeepSign model with another model that predicts the prognostic index by

		DeepSign algorithm model that associates with the results of vital signs		than a prediction of RS prognostic vital signs index	using deep learning techniques while accounting for previous data.
7	(Kuan-Han et al., 2021) Taiwan	To build a machine learning model that can anticipate the in-hospital death rate of non-traumatic adult patients who arrive at the emergency department during different stages of their stay, and to evaluate the effectiveness of other machine learning models and MEWS in comparison.	A Retrospective observational cohort study	Machine learning can predict the incidence of death in the hospital for 48 hours. MEWS's AUPRC performance fell below 0.1, while the machine learning model's AUPRC was 0.317 in 6 hours and 0.2150 in 168 hours, machine learning can predict hospital mortality more than MEWS in adult non-trauma emergency department patients.	Future research can enhance the effectiveness of other machine learning models to produce better clinical outcomes in emergency department patients.
8	(Rojas et al., 2018) Chicago	To develop machine learning to escalate the accuracy of scores in predicting patients who are readmitted to the ICU.	Observational cohort study	Patients who were readmitted to the ICU had an average time to re-admission of 65 hours, and patients who were readmitted to the ICU had the potential to be longer than those who were not readmitted (3.9 days vs 2.9). With 95% confidence, the machine learning derivative model has the highest AUC for predicting a patient's	The addition of research variables is tremendously essential in machine learning models hence, information is obtained about the reasons for entering the intensive care unit.

				return to the intensive care unit (76%).	
9	(Chiew et al., 2019) Singapore	To assess and contrast the effectiveness of machine learning models versus traditional risk stratification tools such as Rapid Sequence Organ Failure Assessment (qSOFA), National Early Warning Score (NEWS), modified early warning score (MEWS), and Singapore ED Sepsis (SED).	Observational study	The application of the machine learning model could enhance the accuracy of forecasting 30-day in-hospital mortality rates for patients displaying symptoms of sepsis in the emergency department, in comparison to utilizing conventional risk stratification methods.	Future research may employ electronic models to assess whether they are capable of helping predict improved clinical outcomes for patients with sepsis.
10	(Rangan et al., 2022) Israel	To create essential equipment with minimal requirements that can utilize lightweight sensors for quick and easy monitoring, automatic and regular running of a sepsis prediction engine, generation of early warnings, and an increased window of time for preventative therapeutic interventions	Retrospective Study	The results demonstrated that combining only heart rate and temperature predicts sepsis 6 hours earlier with greater accuracy, with an area under the curve of 0.94, sensitivity of 82%, and specificity of 85%. similar to alternative predictors of sepsis.	Future research should be conducted to verify the practicality of Vital-SEP in a clinical setting and evaluate the quality improvement and outcomes. A prospective study should be performed to accomplish this.

11	(Arnold et al., 2019) Amerika Serikat	To compare the predictive capabilities of commercially available AI-based EWS models to those of a doctor's clinical evaluation for detecting deterioration in patients admitted to the general internal medicine ward	Prospective observational study	The The combination of physician and EWS forecasts in a linear regression model produces an AUROC of 0.75, which is higher than the prognostic powers of EWS (p;0.05) and physicians (p;0.016). Regarding the ability of EWS and physicians to predict clinical deterioration in patients admitted to the general medicine ward within 24 hours, there is no discernible difference in performance.	Further research is to understand the differences between these predictions, to incorporate them into a risk prediction model together, and to employ them in clinical practice.
12	(Kia et al., 2020) New York	To compare RF models with Modified The early Warning Score (MEWS) uses sensitivity and specificity.	Cohort study single center retrospective	The study revealed that the mortality rate was 3.4%, and the RF model outperformed other models, achieving a sensitivity of 81.6%, specificity of 75.5%, AUC-ROC of 0.85, and AUC-PR of 0.37. The RF model displayed a 37% increase in sensitivity, an 11% increase in specificity, and a 14% increase in AUC-ROC when compared to the conventional MEWS. Furthermore, the RF model could predict mortality up to six hours in advance of	The future study is expected to generate predictions that are judged by discovering hidden patterns and adding even more data

				the event and identify indicators of clinical deterioration.	
13	(Spangler et al., 2019) Swedia	To authenticate the use of a machine learning-based method for creating risk scores that are following hospital outcomes, using a pre-hospital database.	Prospective cohort study	According to research findings, machine learning offers a viable way to enhance prehospital risk assessment accuracy beyond what currently occurs and beyond rule-based triage algorithms.	Further research is recommended to further investigate whether the inclusion of more regular data additions such as free text notes and delivery center call recordings, enhance the prognostic significance of the findings presented here.
14	(Wu et al., 2022) Cina	To create and authenticate a machine-learning algorithm for the early detection of moderate-to-severe cases of ARDS caused by inhalation.	Retrospective derivation cohort	The impact of predicting moderate to severe acute respiratory distress syndrome (ARDS) caused by inhalation six hours before its onset using the machine learning model in conjunction with the primary characteristics derived from three non-invasive vital sign assessments.	Future research is expected to increase the number of patients by expanding the cause of ARDS such as COVID-19.

This article summarizes the themes contained in the application of Artificial Intelligence (AI) models associated with EWS in determining changes in the clinical condition of patients, including the advantages of implementing AI in EWS compared to conventional (article numbers 1,2,3,4,5,6,7, 10, 12). AI classification, types of AI models related to EWS (article numbers 1,2,3,4,9), and accuracy of AI models in predicting patient Quality of Life (article numbers 1,4,6,8,13,14).

THEME 1: The usefulness of implementing AI in a conventional EWS. Reducing additional clinical damage and more serious complications in critical patients can be achieved by identifying AI-based EWS associated with physician prognosis in determining critical patient conditions and predicting clinical status changes earlier (Arnold et al., 2019; da Silva et al., 2021). Sepsis is a common complication in critically ill patients. By merging AI algorithms with vital sign data, it is possible to predict critical patients by calculating the probability of sepsis within six hours. When compared to traditional triage and EWS studies, the effectiveness of the Artificial Intelligence (AI) algorithm can accurately predict the clinical status needs of critical patients using EMS data (95% (Kang et al., 2020). The AI algorithm model with EWS developed into xAI-EWS is presented.

In summary, two individual-based xAI-EWS models were developed that can predict a high probability of developing an acute critical illness. The second population-based xAI-EWS model can predict clinically advanced (sepsis, AKI, and ALI) (Lauritsen, et al., 2020). AI-based alerts using the DeepLearning model with parameters of vital signs can predict more and faster cardiac arrest events with an accuracy of 80%, thereby reducing the incidence of false alarms in hospitals. Early detection of critical patients using EWS, both modified EWS (MEWS) and national EWS (NEWS), has less than optimal accuracy, increasing code blue calling activities in hospitals (Lee et al., 2021; Soudan et al., 2022). Cardiac arrest incidents will result in a rise in the mortality rate among critically ill patients. For this reason, the development of an AI algorithm related to EWS data combined with laboratory results can be employed in predicting the incidence of death in critical patients (Allen et al., 2020; Kia et al., 2020; Kuan-Han et al., 2021; Pirneskoski et al., 2020).

THEME 2: Types of AI Models Linked to Databased. Based on the anticipated outcomes, different types of algorithms can be employed to learn the mapping function between inputs and outputs. Regression and classification algorithms are two categories into which AI algorithms can be subdivided. The latter generates numerical outputs based on a given set of inputs, whereas the former generates a categorical result that indicates the category to which the input set belongs (Soudan et al., 2022).

Subtheme: Machine Learning (ML) Models. ML models originate from computational learning theory and work by constructing data-driven models through paired sample input/output training (Alam et al., 2019).

Random Forest (RF). Several decision trees are implemented by the Random Forest (RF) algorithm to generate predictions from input data. Among the many benefits of RF are its flexibility and resistance to overfitting. With just one hour's worth of input data, this model has proven to be highly accurate in predicting cardiac arrest events (Pirneskoski et al., 2020; Soudan et al., 2022). ML (machine learning) models can increase user intuition by finding hidden patterns in large data sets (Kia et al., 2020).

Subtheme: Deep Learning Model (DL). A deep learning model is heavily reliant on the amount of data that can be analyzed. The likelihood of attaining ideal outcomes increases with the amount of data available (Kang et al., 2020). DEWS, which incorporates three layers of long-term memory (LSTM) to reflect trends in patient vital signs, can be utilized to clarify the merging of DL with EWS (Lee et al., 2021). DL was developed into DEEPSOFA with the TCN model. The xAI-EWS model was designed as a variation of the convolutional neural network

(CNN) recognized as the Convolutional Network (TCN) score, as a predictive model for acute critical illness. The SOFA score is calculated every time one of the model components is updated with a new measurement (Lauritsen, et al., 2020).

Support Vector Machine (SVM). The most effective hyperplane for classifying new data has been identified using the training set of data. The SVM model's benefit is its capacity to manage non-linear classifications, which are employed in regression and clarification. This method's drawbacks encompass the difficulty of determining which machine learning technique is best for non-linear classification and the requirement for a sizable amount of data.

Naive Bayes (NB). A naive Bayes classifier is a statistical algorithm based on Bayes' Theorem that estimates the probability of an event occurring. A statistical method that calculates the likelihood of an event happening that is based on Bayes' Theorem is known as a naive Bayes classifier. According to the Naive Bayes model, predictor values' impact on a specific classification is independent of other predictor values. The basic idea behind the Naïve Bayes classifier is that each feature generates an equal and independent contribution to the result (Soudan et al., 2022).

K Nearest Neighbor (KNN). The KKN classifier attempts to identify samples that are not identified, and then these elements are included in the part of the data closest to the simple majority data (Zhang et al., 2018). The fundamental concept of the Naïve Bayes classifier is that every feature contributes equally and independently to the outcome

Multi-Layer Perceptron (MLP). To classify input vectors into output vectors, Multi-Layer Perceptron (MLP) is a Neural Networks (NNs) implementation that uses an input layer, a hidden layer, and an output layer (Soudan et al., 2022). However, this device does not develop widely and is rarely employed in attachment AI for EWS.

Convolutional Neural Network (CNN). Convolutional Neural Networks (CNNs) are a subset of Deep Learning (DL) algorithms that were developed specifically to automatically identify and extract relevant features for classification from input elements. It is frequently employed in the analysis of both organized and unorganized data. CNN's capacity to efficiently learn and extract features from massive data sets is one of its primary benefits. This is especially true in the healthcare industry, where CNN is frequently utilized to analyze unstructured medical data and put complex models into practice. CNN requires fewer data analyses than other AI algorithm techniques.

THEME 3: Accuracy of AI in EWS in Predicting patient quality of life. According to the study, the application of AI algorithms for predicting the likelihood of critical patient care is highly effective with a success rate of 0.867 (95% confidence interval). According to the study. Additionally, it can be employed to accurately predict prognosis and treatment (Kang et al., 2020). Critical patients frequently experience life-threatening acute respiratory distress syndrome (ARDS), which affects critical patient morbidity and mortality. The development of AI in predicting early ARDS conditions associated with EWS data can be identified quickly. It predicted the onset of moderate to severe ARDS in critically ill patients using AI algorithms. Who are being induced by inhalation (Wu et al., 2022). It was discovered that the most frequently employed AI algorithm in the medical literature is for disease prediction, specifically for conditions like cancer, disorders of the nervous system, heart problems, and cardiac arrest. The trained partition's AI prediction accuracy was 80%, while the test partition's accuracy was 20%. Within the next sixty minutes, the highest prediction accuracy was attained regarding the emergence of a critical CA. Therefore, it is essential to consistently check high-risk patients' vital signs and enter these values into predictive algorithms. This allows a CA to be predicted up to 60 minutes in advance of its occurrence. Medical personnel will therefore be in a better position to act quickly to prevent this from happening. Only one day of data is needed to produce a sufficiently accurate prediction. Therefore, prediction algorithms can start guiding medical staff moderately quickly (Soudan et al., 2022). The trial results mentioned above clarify that internal signs that are connected to vital signs can be utilized. The objective is to predict the vital signs with a high degree of accuracy (above 80%) to predict the Prognostic Index before a significant decline in the patient's condition. Because of this, doctors can start treating patients earlier and achieve better results (da Silva et al., 2021).

The Machine learning algorithm model has significantly better performance accuracy with a receiving curve of 0.76 than MEWS with a receiving curve of 0.58, which can be concluded that the treatment of patients who will return to intensive care after being transferred is more accurate than utilizing machine learning than MEWS in indications of transfer patients from the ICU to the inpatient unit (Rojas et al., 2018). Furthermore, compared to the triage algorithms currently in use in hospitals, machine learning can be used to predict a patient's condition before hospital admission, increasing the accuracy of prehospital risk assessment (Spangler et al., 2019).

Based on this scoping review, the application of AI to EWS shows excellent potential. However, several important research areas need to be explored for these models to be effectively implemented in clinical practice. Potential for Improved Prediction Accuracy: Most of the studies in our review utilized a prediction window between 30 minutes to 72 hours before clinical changes occurred. The length of the model prediction window is essential because a prediction window that is too short will not produce real clinical benefits (it will not give the clinical team enough time to intervene) (Pirneskoski et al., 2020). The results of 14 articles indicate that the worsening of a patient's clinical condition to the point of death frequently results in vital signs changing for the worse before the patient becomes critical and cardiac arrest occurs. This allows predicting critical patients by observing vital signs. Research has also illustrated that abnormalities in these vital signs may begin to appear quite a long time, perhaps even hours before worsening occurs. However, health professionals might require assistance to quickly identify these changes in routine observations. Nevertheless, it is possible to create Artificial Intelligence (AI) systems that can identify these irregularities and estimate the probability of a decline in clinical status that could lead to cardiac arrest. According to Shang, (2021), there is a greater prevalence of literature on artificial intelligence (AI) in medicine than there is in nursing literature reviews. Because of this, artificial intelligence (AI) has many applications that are useful for medical professionals, such as nurses and doctors. Although it is widely recognized for its capacity to aid in the diagnosis and interpretation of medical imaging, nurses—who play a crucial role in the healthcare team's decision-making processes—can make use of additional technologies. However, nurses' adoption of these technologies has been slow, as noted by Pepito et al., (2019). For this reason, a more in-depth study is required regarding AI in EWS which is associated with the TTV results performed by nurses.

The implementation of AI in EWS has an enormous amount of promise to increase the precision of patient critical event prediction. This review's numerous studies demonstrate how AI algorithms, like decision trees and neural networks, can generate predictions that are more accurate in real-time. This implies that early warning systems for medical personnel can be more effectively utilized, enabling prompt and effective action (Barton et al., 2019). An AI algorithm with high accuracy in determining cardiac arrest based on the medical records results is Random Fores reaching 81% in 1 hour predicting cardiac arrest and CNN reaching 84% in 12 hours predicting cardiac arrest (Soudan et al., 2022). To predict early clinical changes and prevent additional clinical damage and more serious complications in critical patients, it is crucial that AI-based EWS identification, which employs machine learning algorithms related to the health prognosis of workers, including nurses, determine the condition of critical patients (Arnold et al., 2019; da Silva et al., 2021). The application of AI in EWS can be used to forecast changes in the clinical status of patients in critical condition before more clinical deterioration and major complications—like sepsis, inhalation-induced ARDS, cardiac arrest, and death—occur. AI algorithms can be applied to help medical professionals identify illnesses and clinical changes in critically ill patients, allowing them to decide what additional interventions are necessary (Kim et al., 2019). Another benefit of using EWS is to help detect physiological abnormalities that cause heart attacks; it is hoped that the ML algorithm model can help reduce this by increasing the detection of patients at risk of heart attack (Rajkomar et al., 2019).

AI has a lot of advantages for the health industry, but because data is limited and subject to change, predictions may be biased. For AI algorithms to generate predictions based on input data, learning models must be used for training. The algorithm being used determines how the training continues. There are two primary categories of AI models: machine learning (ML) and classical AI. While Shallow Learning (SL) and Deep Learning (DL) use nested networks of decision elements to achieve accurate predictions, machine learning (ML) models use deep neural networks to enable decision-making without the need for training pairs (Ongsulee et al., 2018). Deep learning is a machine learning method capable of learning intricate data representations and transforming input data representations into results with a higher level of abstraction (Kapitanova & Son, 2012). Achievement Because the model-building process can eliminate the pre-possessing stage, deep learning techniques are thought to be superior. Deep learning is a type of machine learning that can recognize intricate patterns in data and produce outcomes based only on the data input, without the need for explicit predictors (Rajkomar et al., 2018). The variability in model usage can be attributed to the fact that the predictive performance of models derived solely from historical data is determined by the training dataset (Kong et al., 2016). The analysis of big data can be sampled and integrated with background knowledge employing data processing techniques such as decision trees, random forests, artificial neural networks (ANN), Bayesian networks, and support vector machines (SVM) (Awad et al., 2017).

Retrospective Versus Prospective Evaluation. Since the majority of the research in this review was retrospective, the algorithms' performance in a real-world clinical setting might not be as satisfactory as it would be in a controlled retrospective setting. Furthermore, the degree to which this Early Warning Score (EWS) can detect clinical deterioration that the treatment team has not yet noticed is still being investigated. Even when the risk of deterioration has been accurately identified, doctors frequently disregard warnings about potential clinical deterioration, particularly when they are fatigued. In two case studies, prospective research on artificial intelligence (AI)-based EWS (Arnold et al., 2019) discovered that the use of random forest classifiers in EWS predicted clinical worsening by 75% compared to predictions by physicians 70% Linear regression models combining physician and EWS predictions possessed an AUROC of 0.75, outperforming physicians ($p=0.016$) and EWS ($p=0.05$). Machine learning-based risk scores outperform widely used rule-based triage algorithms and human prioritization decisions in predicting outcomes (Spangler et al., 2019). The results are also similar to those identified by (Pirneskoski et al., 2019) who invented machine learning a value of 84% for the NEWS score in predicting 1-day mortality. Even though the machine learning models presented in the Spangler, 2019 study performed well in prospective validation, they might need to enhance their generalization when utilized in other contexts. If the model is directly applied in other settings, such as a hospital, hospital admissions and guidelines for intensive care may differ, which could lead to biased outcome predictions. These kinds of anomalies are probably also in the predictor variables.

Standardization of Performance Metrics. The primary finding of this review is that the research community does not have generally accepted guidelines for disclosing measurements of performance from different studies. When this happens, it becomes difficult to compare study results meaningfully and, if there is overlap, it is unclear if the most clinically relevant metrics were selected. The majority of the research included in this review report employ Area Under the Receiver Operating Curve (AUROC) as the main performance metric, which is typical of the literature on artificial intelligence.

Strengths of the Review. Although the search strategy was extensive, it only partially addressed particular clinical outcomes, the frequency of sampling, or the screening schedule. The inclusion criteria in this review supported the examination of findings from studies conducted in a variety of clinical settings, including emergency care units and specialist units or wards. This made it possible to identify as many studies as possible examining the use of AI models and vital signs to predict the risk of patient deterioration. This contributes to defining the application of AI-driven prediction models across various patient care contexts with diverse clinical outcomes. Weighted aggregation was employed to compare the artificial intelligence (AI) model's performance with the Early Warning Score (EWS) in cases where the first study's data was available. It indicates the degree to which the accuracy of the models differs in predicting clinical deterioration. the application of AI in EWS is to corroborate detecting physiological abnormalities that cause heart attacks; It is hoped that the AI algorithm in the ML model can help reduce this by enhancing the detection of patients who are at risk of having a heart (Rajkomar et al., 2019). When the evaluation process can assist in analyzing Vital Signs (TTV) results to support decision-making in critical nursing diagnoses and gather crucial patient data efficiently and precisely in critical patient care, artificial intelligence (AI) is used in critical nursing services. Artificial intelligence (AI) is one of the latest technological developments in the healthcare industry and provides new opportunities for providers. Numerous advantages and opportunities are generated by AI integration, such as faster disease prognosis, better disease treatment, enhanced patient participation, and engagement, decreased medical errors and better service quality, reduced medical costs and operational efficiency, and higher productivity for better and maximum outcomes (Lee & Yoon, 2021)

The Limitations is it is essential to acknowledge the various limitations of the review's findings. Initially, a single author managed every step of the process, including the literature search, full-text article feasibility assessment, review inclusion and research data extraction. Second, because studies with positive results are more likely to be published, the results of this review may be influenced by publication bias, as only published studies are included. Third, even though this review included studies from a variety of backgrounds, the heterogeneity in patient populations, clinical practices, and research methodologies among the studies may limit the ability to generalize findings. The definition of clinical outcomes was based on different criteria or using EWS with different aggregate weights, and the sampling procedure and frequency varied between studies, ranging from one-time observations to repeated observations of patients' vital signs. Finally, differences in the Artificial Intelligence (AI) employed in these studies may also result in variations in prediction time windows and other parameters.

4. CONCLUSION

Through a scoping review approach, this study resulted in the application of AI to the Early Warning Score (EWS) system in hospitals that can be employed to enhance the accuracy of predicting changes in patients in critical condition, including cardiac arrest, sepsis, inhalation-induced ARDS events until the patient dies. Because AI models perform better and achieve high accuracy, they are frequently utilized in deep learning and machine learning applications. To achieve the best outcomes, more research must be employed on the application of AI with EWS in critical care patients. This research should include the addition of pain scales and laboratory result parameters to enhance prediction accuracy.

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