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EFFECTIVENESS OF EARLY WARNING SCORE (EWS) IN PRE, INTRA, AND POST DIALYSIS: A SYSTEMATIC REVIEW

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ABSTRACT

The Early Warning Score (EWS) is a crucial tool for detecting early signs of clinical deterioration in hemodialysis (HD) patients. However, previous research has primarily focused on the intra-dialysis phase, necessitating a systematic review to explore the effectiveness of EWS across all phases (pre, intra, and post-dialysis). Objective: This study aims to assess the effectiveness of EWS in detecting complications in hemodialysis patients across these three phases and to evaluate its impact on morbidity, mortality, length of hospital stays, and readmission rates. Methods: This systematic review was conducted following PRISMA guidelines. Literature searches were performed in databases such as PubMed, Scopus, ScienceDirect, ProQuest, and Google Scholar. The keywords used in the search were “Early Warning Score” OR “EWS” AND “Hemodialysis” OR “Renal Dialysis” OR “Dialysis” AND “Pre-dialysis” OR “Intradialysis” OR “Post-dialysis” and can utilize Boolean logic (AND, OR, or NOT) to maximize search results. The screening of articles with respect to limitations including year 2016 - 2024. Results: Out of 1,246 identified articles, 15 studies met the inclusion criteria. The findings indicate that EWS is effective in detecting complications across all hemodialysis phases, with significant improvements in clinical management and reductions in morbidity and mortality rates. Conclusion: The comprehensive application of EWS in the pre, intra, and post-dialysis phases can enhance the safety of hemodialysis patients.

Keywords: early warning score; hemodialysis; systematic review

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INTRODUCTION

Chronic kidney disease (CKD) is one of the global health problems whose prevalence continues to increase, especially due to the increase in cases of diabetes mellitus (DM) and hypertension (Indonesian Renal Registry, 2022). Uncontrolled DM and hypertension can lead to various complications that cause CKD patients to fall into end-stage conditions that require renal replacement therapy treatment, one of which is hemodialysis. Hemodialysis (HD) is a kidney replacement therapy that is widely used in the treatment of end-stage renal disease (ESRD). CKD patients undergoing HD are prone to various complications, such as intradialytic hypotension, arrhythmias, and hyperkalemia, which can increase the risk of morbidity and mortality. Early detection of worsening clinical conditions is one of the key factors to prevent serious complications (KDOQI, 2015).Early Warning Score (EWS) is a very important tool for healthcare providers to recognize and respond to early signs of patient deterioration. The score is calculated based on various physiological parameters and is designed to identify patients at risk of clinical deterioration (Nielsen et al., 2020). EWS has become an integral part of patient monitoring in various healthcare units. The system is designed to identify patients at risk of clinical deterioration, thus allowing healthcare providers to intervene and early management (Wu et al., 2022). The aim of this score is to ensure timely and appropriate management of deteriorating patients in general hospital wards, as delays in treatment or inadequate care can lead to an increase in the number of patients admitted to intensive care units, increased length of hospital stay, cardiac arrest, or death (Dewi et al., 2023). In the context of hemodialysis, the development of a comprehensive EWS can significantly improve the monitoring and evaluation of hemodialysis patients, leading to timely interventions and better outcomes for patients (Lin et al., 2022). EWS has been widely used in various healthcare units, but its application in HD patients is still limited, especially in the pre- and post-dialysis phases. Most studies of EWS in HD patients only focus on the intra-dialysis phase, whereas the pre- and post-dialysis phases also have a significant risk of complications (Cavalier et al., 2022). With the development of technology, there is an opportunity to improve the effectiveness of EWS in all three phases of dialysis. This systematic review aims to evaluate the effectiveness of EWS in detecting complications in the pre-, intra- and post-dialysis phases, and explore the role of technology in improving the accuracy and responsiveness of EWS.

METHOD

Research Design

This study is a systematic literature review (SLR) using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analysis) guidelines, which aims to collect, summarize and report related research findings to identify evidence gaps, and draw conclusions from the existing literature review and describe various instrument developments that address EWS instruments in HD units. Stages included (1) identification of literature through electronic databases, (2) screening and selection based on inclusion-exclusion criteria, (3) study quality assessment, and (4) data synthesis analysis

Search Method

The literature search method used in this systematic review was conducted using search engines: PubMed, Scopus, ScienceDirect, ProQuest, and Google Scholar. The keywords used in the search were “Early Warning Score” OR “EWS” AND “Hemodialysis” OR “Renal Dialysis” OR “Dialysis” AND “Pre-dialysis” OR “Intradialysis” OR “Post-dialysis” and can utilize Boolean logic (AND, OR, or NOT) to maximize search results. The reference list of the main article is also screened for backward citation tracking. The screening of articles with respect to limitations including year (2016-2024), full text and English language, so as to obtain relevant articles.

Inclusion and Exclusion Criteria

The inclusion criteria for the article were:
1) Studies addressing hemodialysis patients with EWS implementation in the pre, intra and post dialysis phases;
2) Quantitative (quasi experimental, case report, cross sectional, RCT and cohort study) or qualitative designs assessing the implementation of EWS in HD patients in the pre, intra and post dialysis phases;
3) Articles that have primary data related to clinical outcomes (e.g. intradialytic complications, incidence of hypotension, readmission, mortality);
4) Taken within the last 5 years, in Indonesian or English, peer-reviewed.
Exclusion criteria for articles were:
1) Studies in populations other than hemodialysis (e.g. peritoneal dialysis patients, kidney transplantation, etc.) or did not address the use of EWS in the context of dialysis,
2) Articles for which the full text is not accessible,
3) Opinion studies, editorials, conference abstracts without empirical data, or languages other than Indonesian/English.

Screening and Selection Process

The screening process followed the PRISMA flow. After removal of duplicates, articles were screened based on title and abstract, then study quality was assessed using tools such as Cochrane Risk of Bias Tool for experimental studies and Newcastle-Ottawa Scale for observational studies. Searching through the keywords above resulted in the number of articles identified including PubMed 251 articles, Science direct 1,090 articles, and google scholar 83 articles and Scopus 3 articles, and Proquest 13 articles, bringing the total to 1,246 articles. Selection based on duplication obtained 384 of the same articles, leaving 687 articles. The screening process based on title identification obtained 642 articles. Furthermore, screening was carried out based on the abstract, 45 articles were obtained. After reviewing the full text articles, 15 articles were left for review. This systematic review aims to collect, summarize and report the findings of related studies to identify evidence gaps, draw conclusions from the review of existing literature and critique various instruments that address research and development of EWS instruments in HD units.

RESULT

Study Selection Process

The following is a flowchart diagram of the study selection process in the figure below:

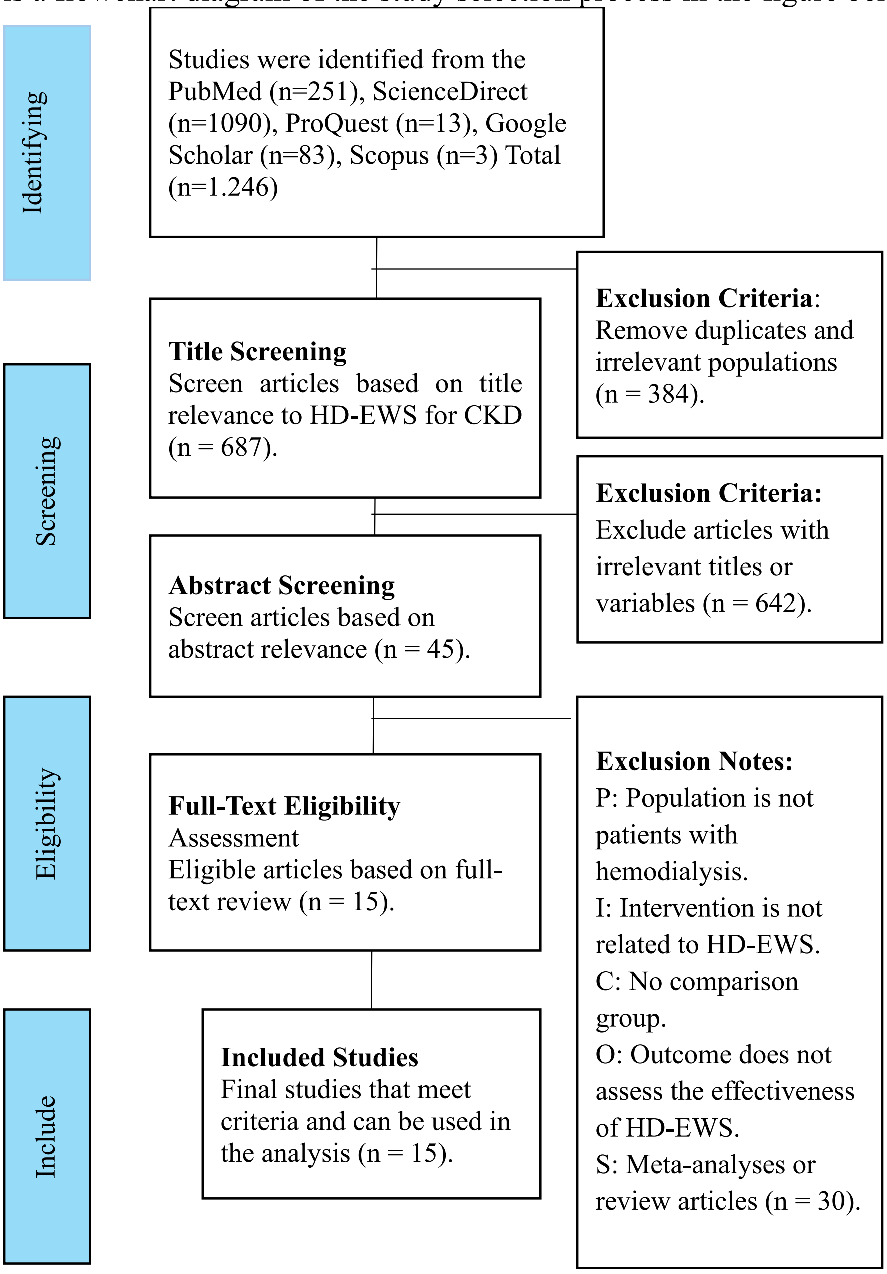

Figure 1 Study Selection Process Using PRISMA

DISCUSSION

Study Characteristics

A total of 15 studies met the inclusion criteria. The included studies consisted of various designs, including 6 retrospective cohort studies, 3 prospective cohort studies, 2 observational studies, 2 development and validation studies, and 2 systematic studies. Sample sizes ranged from 12 to more than 3,900 patients. Most studies used machine learning methods and predictive algorithms to predict adverse events in hemodialysis patients, focusing on variables such as blood pressure, albumin levels, and other physiological parameters. Some studies developed specialized instruments such as early warning systems designed to monitor patient conditions in real-time, including HD-EWS and IoT-based systems. The range of study locations included Asia (n=6), Europe (n=3), and the United States (n=6).

Intervention Characteristics

The interventions carried out in this study were various instrument developments or studies related to Early Warning System (EWS) in hemodialysis patients that were analyzed in the systematic review. The interventions showed a variety of intervention characteristics that reflected the clinical and technological approaches used to improve patient safety. Below are the main characteristics of the implemented interventions:

Table 1.
Evidance Based Practice

No	Title	Method	Result
1	Prediction of Mortality in Hemodialysis Patients Using Moving Multivariate Distance (Liu et al., 2021)	Design: Retrospective cohort study Study: 763 HD patients Variables: 16 biomarkers, including 11 measured every 2 weeks, such as albumin, hemoglobin, creatinine, and others Instrument: eRM Analysis: Multivariate moving distance algorithm, survival analysis, ROC curve analysis	The algorithm achieved 85% accuracy in predicting mortality. Able to identify key predictive factors: blood pressure variations, albumin levels, and inter-dialysis weight gain. Early warning signals were detected 2-3 weeks before critical events. The model showed superior performance compared to traditional statistical methods.
2	An Early Predictive Scoring Model for In-Hospital Cardiac Arrest of Emergent Hemodialysis Patients (Chen et al., 2021)	Design: retrospective cohort Sample: 257 patients Variable: incidence of in-hospital cardiac arrest (IHCA) within 3 days Instruments: Medical record data Analysis: Kaplan-Meier analysis, Log-Rank test	The results showed that this predictive score model had an area under the curve (AUC) of 0.78 in the main group and 0.75 in the validation group. Patients with a score ≥3 had an IHCA risk of 47.2% in the main group and 41.7% in the validation group, while patients with a score <3 had a risk of 18.3% and 7%, respectively. The model is expected to assist healthcare providers in taking necessary preventive measures and allocating resources effectively.
3	Prediction of intradialytic hypotension using pre-dialysis features- a deep learning-based artificial intelligence model (Lee et al., 2023)	Design: Retrospective study Sample: 2,007 participants Variables: Pre-dialysis features including blood pressure before dialysis, targeted ultrafiltration rate, interdialytic weight gain, and history of IDH in the previous session Instrument: medical record data Analysis: Deep learning model development was compared with three other machine learning models: logistic regression, random forest, and XGBoost.	IDH occurred in 5.39% of all HD sessions studied. The deep learning model incorporating data from the previous three sessions showed improved prediction performance and was superior to the other models. The most influential features in predicting SSI were mean systolic blood pressure during the previous session, target ultrafiltration rate, pre-dialysis systolic blood pressure, and

No	Title	Method	Result
		Model performance was evaluated using Matthews correlation coefficient (MCC) and macro-averaged F1 score.	experience of SSI during the previous session.
4	Predicting Quality of Life Changes in Hemodialysis Patients Using Machine Learning: Generation of an Early Warning System (Saadat et al., 2017)	Design: Prospective cohort study Sample: 78 HD patients Variables: Predictor variables included age, gender, monthly income, iron sucrose dose per month, total QoL score at the start of the study, as well as changes over the month in individual domain scores, hemoglobin, and serum albumin. Instruments: A validated Urdu version of the WHOQOL-BREF questionnaire was used to assess QoL, along with the collection of demographic and clinical data through a form completed by the clinician. Analysis: Machine learning algorithms, including decision trees, were used to identify factors associated with a change in QoL of 5% or more over a month.	Factors associated with a 5% or more improvement in QoL included younger age (<19 years) and higher iron sucrose dose (>278 mg/month). A decrease in psychological, physical, and social domain scores contributed to a decrease in QoL by 5% or more. The developed early warning system is expected to assist in the early detection of QoL decline in the hemodialysis population.
5	Construction of an Early Alert System for Intradialytic Hypotension before Initiating Hemodialysis Based on Machine Learning (Hong et al., 2023)	Design: Retrospective study Sample: 3,906 patients Variables: 19 parameters identified through artificial intelligence feature filtering, including demographic data (age, gender, weight), clinical data (primary disease, comorbidities such as hypertension and diabetes), and dialysis-related records (dialysis vintage, weekly hemodialysis frequency, dialysis session time, weight after dialysis, interdialytic weight gain, dry weight, ultrafiltration set, pre-dialysis blood pressure, mean blood pressure, dialysate temperature, dialysate sodium, and dialysate calcium). Instrument: patient medical record data Analysis: The data were divided into training (80%) and testing (20%) sets. Four interpolation methods, three feature selection methods, and 18 machine learning algorithms were used to build the prediction model. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC), and Shapley Additive Explanation was used to explain the contribution of each variable to the best prediction model.	Out of 314,534 dialysis sessions, 142,237 (45.2%) experienced SSI. The best model showed an AUC of 0.812, indicating good prediction performance. An artificial intelligence-based early warning system integrated in dialysis software can be used to predict the occurrence of SSI, enabling relevant interventions to be made in a timely manner.
6	Predicting mortality in hemodialysis patients using machine learning analysis (Garcia-Montemayor et al., 2021)	Design: Retrospective study Sample: 1,571 samples Variables: Demographic data (age, gender), Charlson comorbidity index, and other relevant clinical variables Instruments: patient medical record data Analysis: Predicted mortality at 6 months, 1 year, and 2 years of hemodialysis was calculated using random forest and compared with logistic regression. Model accuracy was evaluated using area under the curve (AUC).	The mortality prediction model obtained with random forest showed adequate accuracy (AUC 0.68-0.73) and was superior to the logistic regression model (AUC 0.007-0.046).
7	Systematic Fluid Assessment In Haemodialysis:	Design: Development and validation study. Sample: 386 participants Variables: Physiological parameters used	RECOVA enables systematic clinical assessment of fluid status, facilitates early recognition of

No	Title	Method	Result
	Development And Validation Of A Decision Aid (Stenberg et al., 2020)	in the clinical assessment of fluid status, such as symptoms of overhydration or dehydration, as well as data from the BIS. Instrument: The developed decision aid, called RECOVA, consists of a scoring system, thresholds and triggers, as well as a decision algorithm Analysis: Content validation was performed through assessment of the relevance and completeness of the items by patient representatives and experts. Reliability was assessed by inter-rater agreement analysis using the Intraclass Correlation Coefficient (ICC).	volume changes, and integration of BIS in target weight management. Inter-rater agreement in symptom assessment was almost perfect (ICC >0.90). Implementation in clinical practice requires staff training, and clinical intervention studies are needed to evaluate the effectiveness of RECOVA in fluid change correction.
8	A New Scoring System For Covid-19 In Patients On Hemodialysis: Modified Early Warning Score (Stolić et al., 2021)	Design: Observational study Sample: 12 Covid-infected HD patient samples -19 Variables: The independent variables in this study include age and arterial hypertension as comorbidities, while the dependent variable is the MEWS (Modified Early Warning Score) score which is used to assess the clinical condition of the patient. Instrument: MEWS Analysis: Mixed Effect Regression model, SPSS	MEWS can be used as a simple and quick tool to assess the clinical condition of hemodialysis patients infected with COVID-19, assisting in clinical decision-making regarding the level of care required.
9	Applying Healthcare Failure Mode and Effect Analysis and the Development of a Real-Time Mobile Application for Modified Early Warning Score Notification to Improve Patient Safety During Hemodialysis (Lin et al., 2022)	Design: Intervention study using the HFMEA (Health Failure Mode and Effects Analysis) system Sample: Total 2500 samples Variables: Vital sign parameters: Respiratory rate, pulse rate, body temperature, blood pressure, blood potassium, C-reactive protein (CRP), and hemoglobin (Hb) level Total MEWS score: A total score calculated from the assessment of the above parameters, where a score of 5 or more indicates clinical risk Instruments: HFMEA, MEWS, ISBAR, mobile application Analysis: HFMEA analysis, Hazard Analysis	The implementation of HFMEA is effective in identifying potential risks during hemodialysis. The use of mobile apps reduces the incidence of emergency resuscitation during hemodialysis and improves communication between medical personnel.
10	Performance of the National Early Warning Score in Hospitalized Patients With Kidney Failure on Maintenance Hemodialysis (Cavalier et al., 2022)	Design: Retrospective cohort analysis Sample: 1,343 patients with renal failure undergoing hemodialysis and 27,562 patients without renal failure, who were hospitalized Variables: NEWS parameters including respiratory rate, oxygen saturation, oxygen supplementation, body temperature, systolic blood pressure, pulse rate, and level of consciousness. Instrument: NEWS Analysis: Pearson test. Statistical analysis was performed to compare the performance of NEWS in predicting clinical worsening between patients with renal failure undergoing hemodialysis and patients without renal failure.	The study found that NEWS performed well in predicting the risk of clinical worsening in patients with renal failure undergoing hemodialysis, with an area under the curve (AUC) comparable to patients without renal failure.

No	Title	Method	Result
11	Early prediction of hemodialysis complications employing ensemble techniques (Othman et al., 2022)	Design: observational Sample: 215 samples Variables: HD complications Instrument: machine learning model Analysis: Models were evaluated based on accuracy in balanced datasets and F1-score in unbalanced datasets. Grid search with five times cross-validation was used to optimize hyperparameters	Random Forest achieved the highest accuracy of 98% with the lowest training time using 12 features. Gradient Boosting showed the highest F1-score in predicting hypotension, hypertension, and dyspnea. Out of 6000 observed sessions, complications occurred in 2874 sessions, while 3126 sessions were complication-free. The results suggest that the model can help Nephrologists in predicting and preventing complications during hemodialysis.
12	Model for Predicting Complications of Hemodialysis Patients Using Data From the Internet of Medical Things and Electronic Medical Records (Hsieh et al., 2023)	Design: analytic observational with retrospective and prospective approach Sample: 1200 HD patients Variables: IoMT and eRM Instrument: Systematic study of various machine learning models used to predict adverse events in hemodialysis patients Analysis: Data from IoMT and eRM were integrated to build prediction models using machine learning algorithms, such as Random Forest, XGBoost, and Deep Learning.	This study shows that the hemodialysis complication prediction model developed using data from IoMT and EMR has high accuracy and can be implemented in clinical practice to improve patient safety. The integration of IoMT technology and big data analysis from EMR opens up new opportunities in hemodialysis patient management.
13	External Validation of the Prediction Model of Intradialytic Hypotension: A Multicenter Prospective Cohort Study (Xiang et al., 2024)	Design: Multicenter prospective cohort study Sample: 2,235 patients in 11 hemodialysis centers in Sichuan Province, Variables: The variables used in the prediction model included pre-dialysis systolic blood pressure, pre-dialysis diastolic blood pressure, age, and history of diabetes mellitus. Instrument: medical record data Analysis: Model performance was evaluated using Area Under the Curve (AUC) to measure discrimination, calibration plot and Brier score to assess calibration, and Net Reclassification Improvement (NRI) and Integrated Discrimination Improvement (IDI) to assess improvement in predictive value after model update. Decision Curve Analysis (DCA) was used to evaluate the clinical benefit of the updated model.	Of the 2,235 patients, 14.6% had IDH. The AUC for the three original prediction models were 0.746, 0.709, and 0.735, respectively. After recalibration and updating, the model showed an increase in AUC to 0.817 with a Brier score of 0.081, indicating improved accuracy and calibration in predicting IDH risk.
14	An early warning system for Hemodialysis complications utilizing transfer learning from HD IoT dataset (Shih et al., 2020)	Design: Development of an early warning system that combines hemodialysis big data analysis with transfer learning from Internet of Things (IoT) datasets to predict complications during hemodialysis. Sample Data was collected from IoT devices used during hemodialysis sessions, including physiological sensors that monitor patients' vital parameters in real-time. Variables: Physiological parameters such as blood pressure, heart rate, body temperature, as well as hemodialysis machine data such as blood flow rate and ultrafiltration.	The developed system successfully identified early signs of hemodialysis complications, enabling timely intervention to improve patient safety. The implementation of this system shows potential in improving patient monitoring and clinical response during hemodialysis sessions.

No	Title	Method	Result
		Instrument: An integrated system that collects data from IoT devices and applies deep learning algorithms for data analysis. Analysis: A deep learning model with transfer learning is used to analyze physiological data and detect patterns that indicate potential complications during hemodialysis.	
15	Application of early warning signs to physiological contexts: a comparison of multivariate indices in patients on long-term hemodialysis (Legault et al., 2024)	Design: Comparative study Sample: 63 patients undergoing hemodialysis Variables: Five autocorrelation (AC)-based, six variance-based, one cross-correlation-based, and three combined AC and variance-based EWS. Instruments: Periodically collected measurements of physiological parameters from hemodialysis patients, including blood biomarkers and other vital signs. Analysis: Evaluations were conducted by measuring correlations between indicators, trends before death, and predictive power of mortality, both individually and in combination.	The variance-based indicator showed a stronger correlation ($r = 0.663 \pm 0.222$) compared to the AC-based indicator ($r = 0.170 \pm 0.205$) and a sharper increase before death. Two variance-based indicators had HR95 > 9, but their combination did not significantly increase the area under the receiver-operating curve (AUC) compared to individual use (AUC = 0.798 vs. 0.796 and 0.791). Although some indicators did not perform well individually, their addition to the best-performing indicators improved the predictive power, suggesting that the combination of indices can capture a wider range of dynamic changes in the system.

Synthesis Analysis

The findings based on a literature study conducted on 15 articles show that:

1. Effectiveness of EWS in the Pre-Dialysis
   EWS is effective in detecting the risk of complications in the pre-dialysis phase, allowing early intervention to prevent worsening of the patient's condition. This was revealed by Liu et al. (2021) by using Moving Multivariate Distance to predict mortality in hemodialysis patients, showing that EWS can identify high risk before dialysis, while Lee et al. (2023) used a deep learning-based model utilizing pre-dialysis features to predict intradialytic hypotension (IDH) with high accuracy, demonstrating the potential of EWS in detecting risk before dialysis sessions.
2. Effectiveness of EWS in Intra-Dialysis phase
   Chen et al. (2021) developed a predictive model for in-hospital cardiac arrest in hemodialysis patients, showing that EWS can be used to monitor the patient's condition in real-time during dialysis. This analysis is supported by a study conducted by Hong et al. (2023) on an early warning system for SSI built on machine learning showing the ability to detect complications during hemodialysis sessions and a study by Othman et al. (2022) that used ensemble techniques to predict hemodialysis complications, showed the effectiveness of EWS in the intra-dialysis phase. This suggests that EWS in the intra-dialysis phase is effective in detecting complications early, with the use of technology that improves accuracy and speed of response.
3. Effectiveness of EWS in the Post-Dialysis phase
   In the post-dialysis phase, a study conducted by Saadat et al. (2017), developed an EWS system to predict changes in the quality of life of hemodialysis patients, showing that EWS can be used to evaluate post-dialysis outcomes. Which means that EWS is also effective in evaluating and predicting post-dialysis outcomes, assisting in advanced treatment planning to improve patients' quality of life.
4. Use of Conventional Early Warning Scores in Hemodialysis
   Several studies assessed the effectiveness of existing early warning scores, such as the National Early Warning Score (NEWS) and Modified Early Warning Score (MEWS), in

detecting clinical worsening in HD patients. The study by Cavalier et al. (2022) found that NEWS has good predictive accuracy in assessing clinical worsening in patients with renal failure undergoing hemodialysis compared to patients without renal failure. In addition, Stolic (2021) developed a modified score system for HD patients with COVID-19 using MEWS, which was shown to be helpful in the classification of disease severity and the need for further medical intervention. So conventional early warning scores can be used effectively in the context of hemodialysis, although they need to be adapted to patient characteristics for better results.

5. The role of technology in improving EWS
   Technology plays an important role in improving the effectiveness of EWS, enabling real-time monitoring and more accurate prediction of hemodialysis complications. The integration of IoT and machine learning has improved the accuracy and responsiveness of EWS. The early warning system developed by Shih et al. (2020) utilized transfer learning from IoT datasets to detect hemodialysis complications. Another study conducted by Hsieh et al. (2023) who used data from the Internet of Medical Things (IoMT) and electronic medical records to predict hemodialysis complications, showed that technology integration can improve the accuracy of EWS. And a model developed by Lin et al. (2022), which uses a mobile application for EWS notification, which improves communication and response to patient conditions.

Clinical Implications

Implementation of EWS EWS tailored to the phase of dialysis can improve early detection of complications and reduce morbidity and mortality of HD patients. Training healthcare workers in interpreting EWS and the use of technologies such as IoT and machine learning can improve the effectiveness of early warning systems.

CONCLUSION

Based on this systematic review, EWSs show effectiveness in detecting complications in the pre-, intra-, and post-dialysis phases. Integration of technologies such as IoT and machine learning can improve the accuracy and responsiveness of EWS, especially in predicting complications such as intradialytic hypotension.

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