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The value of artificial intelligence in predicting the prognosis of acute respiratory distress syndrome: a systematic review and meta-analysis

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ADMINISTRATIVE INFORMATION

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Review Stage at time of this submission - Preliminary searches.

Conflicts of interest - None declared.

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Amendments - This protocol was registered with the International Platform of Registered Systematic Review and Meta-Analysis Protocols (INPLASY) on 02 May 2024 and was last updated on 02 May 2024.

INTRODUCTION

Review question / Objective P: Patients diagnosed with acute respiratory distress syndrome according to the Berlin definition. I: Prognostic model of acute respiratory distress syndrome. C: Patient death. O: Diagnostic accuracy evaluation, including sensitivity, specificity, prediction value and likelihood ratio. S: Diagnostic accuracy Test.

Rationale Artificial intelligence (AI) is an emerging technology that has demonstrated strong performance across various industries. Building predictive models is an important capability of AI. Numerous studies have explored AI-based models for predicting ARDS mortality. However, the findings from these studies are inconsistent. Some studies suggest that the predictive power of AI is exceptional. Some do not show superior performance of AI algorithms compared to traditional logistic regression (LR). Consequently, evidence-based support for applying AI in ARDS mortality prediction remains limited.To address this gap, our study systematically evaluated the performance of AI algorithms in predicting ARDS mortality through a meta-analysis. We hope that our findings will provide help and suggestions for the promotion and application of AI in this field.

Condition being studied Acute respiratory distress syndrome (ARDS) is a severe condition characterized by profound respiratory failure and a high mortality rate. In clinical practice, ARDS rarely occurs in isolation; rather, it often arises as a consequence of underlying conditions such as sepsis, trauma, pancreatitis, and other related diseases. The Berlin criteria define ARDS based on acute lung injury, bilateral chest infiltrates, and hypoxemia not fully attributable to other factors.

For clinicians, reliable mortality prediction in ARDS patients is crucial. Despite existing predictive models that incorporate multiple variables thought to impact prognosis, accurately forecasting mortality in ARDS patients remains challenging.

METHODS

Search strategy ((ARDS) OR (acute lung injury) OR (acute respiratory distress syndrome)) AND (mortality) AND (prediction) AND ((AUC) OR (sensitivity) OR (specificity)).

Participant or population Patients diagnosed with acute respiratory distress syndrome according to the Berlin definition.

Intervention AI prognostic model of acute respiratory distress syndrome.

Comparator Traditional logistic regression prognostic model of acute respiratory distress syndrome.

Study designs to be included Diagnostic accuracy Test.

Eligibility criteria Inclusion Criteria: patients aged >18 years; patients diagnosed with ARDS based on the Berlin definition; mortality prediction model establishment using AI or LR algorithms with two or more variables; collection of modeling variables within 48 hours after ARDS diagnosis; models need to be validated internally or externally. In AI research, it is difficult to conduct independent external validation due to limited conditions, so validation methods such as K-fold cross-validation or leave-one-out method are utilized. We cannot ignore the contributions that these studies have made. However, we need to consider overfitting from the perspective of evidence-based medicine. Therefore, studies without even internal validation are excluded.Exclusion Criteria: use of specialized molecular markers not readily available in the modeling process; unavailability of data necessary for meta-analysis; Other types of study, such as meta-analysis, review, guideline, and expert comments.

Information sources Web of Science, Embase, Pubmed, Scopus and EBSCO.

Main outcome(s) A standardized form will be used for data extraction, capturing essential details such as title, author, publication date, nationality, study type, algorithm, modeling data type (clinical data, imaging data, or both), modeling cohort size, validation type (internal or external validation), ARDS severity, and counts of true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN). If the study documents multiple machine learning methods, we will register the model with the highest diagnostic accuracy.

Data management EndNote20 management program.

Quality assessment / Risk of bias analysis We will independently evaluate all included studies using the modified quality assessment of diagnostic accuracy studies (QUADAS-2) tool. This assessment focused on applicability to the review question and risk of bias. The evaluation was conducted by at least two authors. Deek's funnel plot was employed for assessing publication bias.

Strategy of data synthesis First, We conducted subgroup analysis and regression analysis on the included models to investigate the factors influencing their sensitivity and specificity.
Second, we conducted a meta-analysis of diagnostic tests for the subgroups generated by different factors. We employed a bivariant mixed-effects model for meta-analysis. This model considers both fixed- and random-effects models, effectively managing heterogeneity across studies and accounting for the correlation between sensitivity (SEN) and specificity (SPE), resulting in more robust and reliable results. We compared differences in model accuracy across subgroups. The bivariate mixed-effects model incorporated SEN and SPE as well as the negative likelihood ratio (NLR), positive likelihood ratio (PLR), diagnostic odds ratio (DOR), and 95% confidence intervals (95% CI). We generated a summarized receiver operating characteristic (SROC) and computed the area under the curve (AUC).

Subgroup analysis We conducted subgroup analysis and regression analysis on the included models to investigate the factors influencing their sensitivity and specificity. The parameters of subgroup analysis are modeling data type (clinical data, imaging data, or both), modeling cohort size, validation type (internal or external validation) and ARDS severity.

Sensitivity analysis We performed sensitivity analysis by subgroup analysis.

Language restriction No language restriction.

Country(ies) involved China.

Keywords ARDS; AI; mortality; prognosis.

Contributions of each author

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