INPLASY PROTOCOL

To cite: Bacci et al. A systematic review of artificial intelligence models for acute kidney injury prediction. Inplasy protocol 202330025. doi: 10.37766/inplasy2023.3.0025

Received: 07 March 2023

Published: 07 March 2023

Corresponding author:
Marcelo Rodrigues Bacci

mrbacci@yahoo.com

Author Affiliation:
Centro Universitario Faculdade de Medicina do ABC.

Support: **None.**

Review Stage at time of this submission: **Piloting of the study selection process.**

Conflicts of interest:
None declared.

A systematic review of artificial intelligence models for acute kidney injury prediction

Bacci, MR[1]; Minczuk, CV[2]; Fonseca, FLA[3].

Review question / Objective: **We performed a systematic review of the use of AI and ML to build AKI prediction models in hospitalized patients.**
Condition being studied: **Acute kidney injury prediction models efficacy.**
Eligibility criteria: **Manuscripts written in english language with abstract available until the 6th of March. The search strategy should adress the MesH terms in the title and abstract sections.**

INPLASY registration number: This protocol was registered with the International Platform of Registered Systematic Review and Meta-Analysis Protocols (INPLASY) on 07 March 2023 and was last updated on 07 March 2023 (registration number INPLASY202330025).

INTRODUCTION

Review question / Objective: **We performed a systematic review of the use of AI and ML to build AKI prediction models in hospitalized patients.**

Rationale: **Acute kidney injury (AKI) is a significant condition responsible for a worse prognosis in hospitalized patients. Several definitions have been developed to provide an accurate and unified diagnosis and staging for AKI, but massive inconsistency exists among them (1). The estimative of glomerular function (eGFR) is the standard method to stage kidney damage(2). Still, equations give a precise picture of stable patients, which differs from the critical care AKI situation, which encompasses unstable patients (2). Serum creatinine (SCr) is the biomarker for AKI diagnosis and eGFR estimation; however,**

its levels are affected by the sex and muscular content of the individuals, and the increase does not happen in AKI early stages(3). Urine output is the other component to the definition of AKI across etiologies but also depends on observing the amount of urine produced during the hospitalization recognition of AKI affects the outcome of patients, treatment duration, and correct drug dose (3) Early recognition of AKI with prediction scores makes personalized patient stratification with targeted biomarkers possible depending on AKI etiology and directed therapy in the early stage (3–5)
Machine learning (ML) is a subdivision of artificial intelligence (AI) focused on comprehending and developing learning methods that use data to enhance task performance. To generate predictions or choices without being explicitly taught, ML algorithms develop a model based on sample data, often known as training data(6). Artificial intelligence and ML in health sciences are new research topics in outcome prediction, diagnosis, and image interpretation and have also been used in AKI(7). Apart from using ML to predict AKI, there is heterogeneity between the studies analysis that use different training variables and databases. An overview of all published material so far has yet to be made.

Condition being studied: Acute kidney injury prediction models efficacy.

METHODS

Search strategy: The electronic search used the text and MeSH terms “acute kidney injury,” AND “machine learning” AND “artificial intelligence” in the title or abstract. Articles should be in english and available to analysis. Only humans trials were included and no time barrier was added.

Participant or population: Hospitalized adults patients with acute kidney injury. Patients need to have more than 18 years.

Intervention: Use of artificial intelligence or machine learning methodology to diagnose AKI.

Comparator: Kidney Disease Improving Global Outcomes (KDIGO) criteria served as default to AKI diagnostic and the AI models built were considered for comparison between them to evaluate their performance.

Study designs to be included: Clinical trials in humans.

Eligibility criteria: Manuscripts written in english language with abstract available until the 6th of March. The search strategy should adress the MesH terms in the title and abstract sections.

Information sources: The electronic databases searched: Medline (Pubmed); EMBASE; Cochrane ; Web of Sciense until 6th of march of 2023.

Main outcome(s): The primary outcomes were the results of the Area Under the Receiver Operating Curves (ROC-AUC) to validate the models created to effectively diagnose and predict AKI using the more relevant variables across the AKI etiologies.

Quality assessment / Risk of bias analysis: We assessed the manuscript´s methodological quality using the risk of bias, the second version (RoB2) developed by the Cochrane collaborators, which encompasses five key domains: bias arising from the randomization process, bias due to deviations from the intended intervention, bias due to missing outcome data, bias in measurement of the outcome, bias in selection of the reported result (9). Manuscripts were classified according to the risk of bias: high risk, some concerns, and low risk. Manuscripts with an increased risk of bias were excluded from the final selection. The Shapley value assessed internal observation of the black box of the results for each study, a tool to interpret the impact of each variable for the given external outcome. There was no need for ethical submission of this study as all

the analyses were made in previously published manuscripts.

Strategy of data synthesis: Two independent evaluators searched four electronic databases: EMBASE, MEDLINE, Web of Science, and Cochrane Library until 30 January 2023, using combined MeSH terms. A third evaluator chose the manuscript when the first evaluators disagreed. Manuscripts were reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (8). The two reviewers extracted the data independently, with the reading of the full abstract and manuscript. Methodology for AKI diagnostic by KDIGO criteria, type of AI model used, type of database used, and obligation to compare AI models with the AUC results. The AI models chosen were logistic regression (LR), random forest (RF), eXtreme gradient boosting (XGBoost), decision tree (DT), support vector machine (SVC), naive Bayes (NB), gradient boost machine (GBM) and deep learning (DL). Manuscripts were excluded if they used only analysis by clustering of AKI cases, not using a comparison between models of ML, and with a proportion higher than 10% of missing data.

Subgroup analysis: After the studies selection a table was created with the main AKI etiologies found, and the result of the AUC of each one of the ML models tested.

Sensitivity analysis: No sensitivity analysis was made.

Language restriction: No language restrictions.

Country(ies) involved: Brazil.

Keywords: machine learning; artificial intelligence; acute kidney injury.

Dissemination plans: We plan to publish the manuscript.

Contributions of each author:

Author 1 - Marcelo Rodrigues Bacci - Idealization of the study; writing of the manuscript ; choice of the manuscripts.
Email: mrbacci@yahoo.com
Author 2 - Catarina Viggiani Bicudo Minczuk - Choice of the manuscripts; methodology idealization.
Email: catarina.minczuk@aluno.fmabc.net
Author 3 - Fernando Luiz Affonso Fonseca - Review of the final version of the manuscript; performed analysis of the articles chosen when there was divergence among the first authors.
Email: profferfonseca@gmail.com