



# Machine learning model for predicting kidney replacement therapy dependence from acute kidney injury requiring dialysis in critically ill patients

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## Introduction

AKI requiring Kidney Replacement Therapy (KRT) in critically ill patients carries a high risk of morbidity and mortality. Following AKI, patients who require dialysis may progress to CKD with long-term dialysis. This condition significantly affects the patient’s quality of life. Using a Machine learning model, the new approach to developing a prediction model may enhance the accuracy of predictions more than traditional statistics for informing patients and their families to support decision-making and enable physicians to plan their patients appropriately.

## Objectives

To develop and validate a prediction model using a machine learning model and traditional statistics to predict KRT dependence following AKI in critically ill patients.

## Methods

A retrospective cohort study at Ramathibodi Hospital between January 2014 and December 2023. Data on demographics, comorbidities, laboratory results, and clinical assessments were collected. The machine learning approach used XGBoost to develop the prediction model. In contrast, the traditional statistic approach used multivariate logistic regression analysis. The final model's performance was evaluated with a divided subgroup using ROC curves and confusion matrix approaches to develop and cross-validate prediction models for KRT dependence.

## Results

Among 615 patients with AKI-D, the mean age was 68.6 years, 54.3% were men, and 20.8% had CKD stage IV. KRT dependence was observed in 14.6% of patients, while 53.6%of patients had died. The model effectively identified patients at risk of KRT dependence within 90 days after initiation. Multivariate analysis demonstrated that CKD stage and preexisting renal disease increased the risk of KRT dependence, whereas metformin used and urinary tract infection served as protective factors. While machine learning had key predictors included CKD stage, coronary artery disease, dyslipidemia, calcium channel blocker use, antiplatelet use, BUN, hemoglobin, WBC >12,000, abnormal heart rate (>120 or <60), and the presence of proteinuria. The XGBoost model achieved a sensitivity of 52%, a specificity of 84%, and an AUROC of 0.76.

## Results

Table 2 : Multivariate Analysis for prediction of KRT dependence after AKI-D

KRT dependent	Odds ratio	95 % CI	P value
CKD stage			
CKD stage 2	1.02	0.21-4.90	0.978
CKD stage 3a	2.73	0.63-11.91	0.181
CKD stage 3b	9.28	2.54-33.96	0.001
CKD stage 4	17.89	4.99-64.14	0.001
Metformin	0.21	0.08-0.56	0.002
UTI	0.29	0.1-0.87	0.027
Renal disease	7.01	0.94-52.08	0.057

Table 5 : Performance of prediction model compared traditional statistic by multivariate logistic regression between machine learning model by XGboost

Statistics	Traditional (Multivariate logistic regression)	Machine learning (Xgboost)
Sensitivity	0.78	0.52
Specificity	0.76	0.84
PPV	0.57	0.6
NPV	0.87	0.79
Area under ROC	0.76	0.76

Figure 3 : Final prediction model for calculator of KRT dependence

Demographic data

Sex

☐ Female

☐ Male

Age

Patient status

CKD stage

CAD

☐ Yes

☐ No

Kidney disease

☐ Yes

☐ No

DLP

☐ Yes

☐ No

CCB

☐ Yes

☐ No

Antiplatelet

☐ Yes

☐ No

Vital sign and Laboratory test

HR >120 or < 60

☐ Yes

☐ No

GCS score

Hemoglobin

BUN

WBC > 12,000

☐ Yes

☐ No

Proteinuria

☐ Yes

☐ No

Calculate KRT dependence

## Conclusion

The machine learning model approach shows promise in predicting KRT dependence, potentially guiding clinical decisions and improving patient outcomes.