

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal



Volume 5, Issue 1, September 2025

The Review on XAI-Driven Kidney Transplant Prediction

Pankaj Karhade¹, Gayatri Jadhav², Harish Patil³, Praful Rasal⁴, Prof. N. V. Kapde⁵, Prof. A. S. Nalge⁶
Department of AIML (Artificial Intelligence & Machine Learning)¹⁻⁶

Loknete Gopinath Munde Institute of Engineering Education & Research (LoGMIEER), Nashik, India

Abstract: Kidney transplantation is the best treatment for end-stage renal disease patients, with better survival rates and quality of life compared to dialysis. Yet, predicting the success of a transplant is still difficult due to the presence of various factors like donor-recipient matching, immunological reactions, patient health status, and post-operative management. Statistical and machine learning models have been employed for outcome prediction, but their "black- box" nature restricts clinical trust since they do not provide explanations for predictions. In healthcare, where transparency and accountability are paramount, this lack of interpretability is a hindrance to adoption.

Explainable Artificial Intelligence (XAI) has been proposed as a solution to overcome this limitation. XAI not only enhances predictive performance but also offers insights into the most impactful features influencing outcomes. For example, in kidney transplant prediction, XAI can identify important variables like donor age, HLA matching, comorbidities, and blood type compatibility, making predictions easier to validate and interpret. This interpretability enables clinicians to develop confidence in AI-supported decisions, facilitates patient counseling, and improves post-transplant care planning.

This review paper discusses the applications of XAI in kidney transplant prediction, reviews recent trends in research, and discusses advantages like enhanced trust and transparency. It also points out challenges like data quality, generalization across populations, and integration into clinical practice. The paper concludes by outlining future directions for XAI in promoting personalized and reliable transplant care...

Keywords: Kidney Transplant, Explainable Artificial Intelligence (XAI), Machine Learning in Healthcare

I. INTRODUCTION

Kidney transplantation is the most effective treatment for end-stage renal disease, with improved survival and quality of life compared to dialysis. Nevertheless, it is difficult to predict the success of a transplant, as it is influenced by numerous factors like donor-recipient matching, patient condition, immune system response, and post-transplant care. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have been used to tackle this challenge, as they can process large medical datasets and identify patterns that physicians might overlook. However, most AI models are like "black boxes," providing answers without revealing how they were obtained. This lack of transparency diminishes trust in AI systems, particularly in medicine, where transparent reasoning is crucial. Explainable Artificial Intelligence (XAI) provides a solution by making AI decisions more transparent. In kidney transplant prediction, XAI can identify which features—like age, donor condition, or blood group compatibility—affect the outcome. This not only enhances trust but also assists clinicians in making informed decisions. This paper discusses the application of XAI in kidney transplant prediction, its advantages, current limitations, and potential to enhance medical decision-making and post-transplant care.

DOI: 10.48175/568



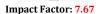






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II. LITERATURE REVIEW

N O	AUTHOR (S) / YEAR	STUDY FOCUS	DATASET / SAMPLE SIZE	MODEL USED	XAI METHOD	KEY FINDINGS
1	FABRETI OLIVEIR A ET AL. (2024)	EARLY GRAFT LOSS PREDICTION IN KIDNEY TRANSPLANT RECIPIENTS	N = 627	XGBOOST	SHAP	AUC ~0.84; KEY PREDICTORS: DISCHARGE CREATININE, BMI, AGE, BK VIRUS INFECTION.
2	ALI ET AL. (2025)	UK LIVE-DONOR KIDNEY TRANSPLANT OUTCOME PREDICTION (3–10 YEARS GRAFT SURVIVAL)	12,661 LIVE DONOR CASES (2007–2022)	XGBOOST	FEATURE IMPORTANCE & CALIBRATION	AUC ~0.75; STRONG CALIBRATION; USEFUL FOR DONOR SELECTION.
3	UNOS STUDY (2024)	DECEASED- DONOR KIDNEY TRANSPLANT OUTCOME PREDICTION	>150,000 TRANSPLA TS	DEEP COX MIXTURE MODEL	SURVIVAL ANALYSIS (INTERPRETAB LE RISK SCORES)	OUTPERFORMED KDPI SCORING; BETTER AUC (~0.67) AND CALIBRATION; IMPROVED ALLOCATION.
4	ICU-AKI MODEL (2024)	ACUTE KIDNEY INJURY PREDICTION IN ICU PATIENTS	MIMIC-IV DATASET	XGBOOST	SHAP & LIME	AUC ~0.816; TOP PREDICTORS: SOFA SCORE, MECHANICAL VENTILATION
5	JAWAD ET AL. (2024)	CHRONIC KIDNEY DISEASE (CKD) PROGNOSTICS	CLINICAL DATASET (SIZE NOT SPECIFIED)	RANDOM FOREST, XGBOOST	EXPLAINABLE FEATURE IMPORTANCE	XGBOOST SHOWED ~98% FIDELITY IN EXPLANATIONS; USEFUL FOR EARLY CKD INTERVENTIONS.

TABLE 1: LITERATURE SURVEY

III. PROPOSED METHODOLOGY

The purpose of this review is to analyze recent advancements in the application of Explainable Artificial Intelligence (XAI) for kidney transplant prediction. The methodology adopted follows a structured review process to ensure that the findings are comprehensive, reliable, and representative of current research trends.

Literature Search Strategy Relevant research articles were collected from widely recognized academic databases, including PubMed, IEEE Xplore, ScienceDirect, SpringerLink, and arXiv. In addition, specialized biomedical sources such as BioMed Central and nephrology-specific journals were also explored. Keywords such as "kidney transplant prediction," "explainable artificial intelligence," "XAI in healthcare," "graft survival prediction," and "machine learning in transplantation" were used to retrieve papers published between 2020 and 2025, with an emphasis on the latest work from 2023 onwards.

DOI: 10.48175/568

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Volume 5, Issue 1, September 2025

Impact Factor: 7.67

Inclusion and Exclusion Criteria Inclusion: Studies that applied machine learning or AI to kidney transplantation and explicitly incorporated explainability methods (e.g., SHAP, LIME, interpretable models). Both retrospective analyses and large-scale registry-based studies were considered.

Exclusion: Studies that used AI without addressing interpretability, opinion pieces without empirical validation, or papers not directly related to kidney transplant outcomes.

Data Extraction For each study, details such as dataset size, model used, explainability technique applied, evaluation metrics (AUC, C-index, calibration), and clinical insights were extracted. Special focus was given to how interpretability contributed to clinical trust, decision support, and outcome improvement.

Analysis Approach The selected studies were categorized based on prediction tasks (e.g., graft survival, early graft loss, donor-recipient matching, readmission, and adverse outcomes). Both the technical contribution (AI/XAI methods) and the clinical significance (impact on decision-making, patient care) were analyzed.

This structured methodology ensured that the review not only captured the technical progress in XAI-driven models but also highlighted their practical implications for clinical decision-making in kidney transplantation.

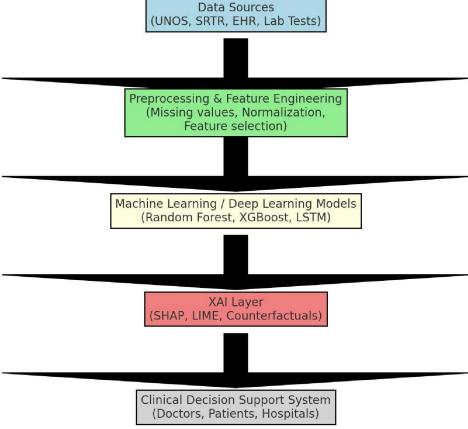


FIG. 1: SYSTEM ARCHITECTURE

IV. RESULT AND DISCUSSION

The studies discussed herein underscore the fact that XAI-powered models offer better performance and better interpretability in kidney transplant prediction. Models like XGBoost and Deep Cox Mixture reliably outperformed conventional scoring systems like KDPI, with AUCs ranging from 0.75 to 0.84 on different datasets. Notably, explainability methods like SHAP and LIME uncovered essential predictors such as donor age, BMI, creatinine, and clinical comorbidities, thus promoting clinician confidence and decision-making. These approaches not only enhanced predictive performance but also enabled patient-specific explanations, facilitating fair allocation and early intervention

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approaches. Yet challenges persist in handling heterogeneity of data, bias risks, and explanation complexity. In total, XAI methods demonstrate strong potential for closing the gap between predictive performance and explainability and are worthwhile tools for future transplant decision support.

V. APPLICATION

XAI-based kidney transplant prediction models are used in donor-recipient matching, risk stratification, and clinical decision support. They increase transparency, boost clinician trust, and aid patient counseling. Moreover, these models guide policy decisions, assist equitable allocation, and yield relevant insights for research and medical education.

- Donor–Recipient Matching: Transparent predictions drive better organ allocation decisions.
- Risk Stratification: Makes it possible to identify patients at high risk of graft failure, rejection, or readmission.
- Clinical Decision Support: Offers interpretable dashboards in EHRs for real-time prediction.
- Trust & Transparency: Ensures clinicians comprehend vital risk factors, enhancing use of AI technology.
- Policy & Allocation: Exposes systemic problems (e.g., donor nonuse, disparities) to better inform guidelines.
- Patient Counseling: Facilitates shared decision-making through transparent, patient-comprehensible explanations.

VI. FUTURE WORK

- 1. Generalization & Validation Test models across multi-center, international datasets to ensure reliability and fairness.
- 2. Data Integration Combine clinical, genomic, and imaging data for more personalized and accurate predictions.
- 3. Clinical Deployment Develop user-friendly dashboards and integrate models into EHRs for real-time decision support.

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