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ORIGINAL RESEARCH

Risk Prediction of Postoperative Renal Dysfunction Based on Preoperative Lipid Profiles in Renal Transplant Recipients: A Retrospective Cohort Study

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Introduction: Renal transplant recipients (RTRs) are at high risk of renal dysfunction, and one contributing factor may be abnormal blood lipids. This study aimed to establish a risk prediction model using machine learning (ML).

Methods: This retrospective cohort study recruited 345 RTRs and followed up for one year. Patients' demographic and clinical characteristics were retrieved from the electronic medical record system. The cohort was randomly split into training (n = 276) and validation (n = 69) groups at a 4:1 ratio. Predictors of renal dysfunction were determined using three ML models: RandomForest, XGBoost, and LightGBM.

Results: During the one-year follow-up, 193 (55.9%) patients developed renal dysfunction. Among 20 demographic and clinical variables screened, five were identified as significant predictors: age, gender, HDL-C, non-HDL-C, and LDL-C. A nomogram was developed as a visual predictive tool to present the interplay between these variables graphically. It demonstrated good diagnostic performance, with an area under the curve (AUC) of 0.87 (95% CI, 0.85–0.89) in the training group and 0.81 (95% CI, 0.78–0.83) in the validation group.

Conclusion: Our study developed a risk prediction model to identify RTRs at high risk of renal dysfunction based on preoperative lipid profiles, which is crucial for optimizing patient management and improving the prognosis.

Keywords: kidney transplantation, renal dysfunction, eGFR, risk prediction, blood lipid levels, machine learning, nomogram

Introduction

Kidney transplantation is the best treatment option for end-stage renal disease.[1] Despite its well-demonstrated benefits in improving the quality of life and prolonging life expectancy, renal dysfunction is a frequent complication.[2] Recent estimates show that the rate of functional graft death is 12%, graft loss is 41%, and the cumulative mortality rate reaches 37% ten years after kidney transplantation.[3] Identifying possible risk factors for renal dysfunction is crucial in initiating early prevention among renal transplant recipients.

Increasing evidence suggests that abnormal blood lipids can lead to a reduced estimated glomerular filtration rate (eGFR) and renal dysfunction, which may further contribute to graft failure and affect long-term survival in RTRs.[4–6] Some common blood lipids associated with renal dysfunction include low-density lipoprotein cholesterol (LDL-C), high-density lipoprotein cholesterol (HDL-C), and non-high-density lipoprotein cholesterol (non-HDL-C). Although the international guidelines recommend controlling LDL-C levels for lipid-lowering treatment, the efficacy in preventing

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postoperative complications among RTRs remains uncertain.[7,8] In addition, renal transplant recipients generally have low HDL-C and high non-HDL-C, significantly increasing the risk of renal dysfunction, yet the mechanism remains unclear.[9–11] A reliable and cost-effective risk prediction model is thus needed to establish the associations between various lipid profiles and renal dysfunction among RTRs to inform further prevention and intervention efforts.

Machine learning (ML) is an efficient data analytics method that enables machines to learn autonomously without explicit programming, which has been widely applied in the medical field to predict health outcomes.[12] ML can discover the relationships and interactions between variables, therefore accurately determining the risk threshold for disease occurrence.[12] Some ML-based predictive models have been developed to evaluate the renal prognosis of various renal diseases.[13,14] However, current prediction models for renal dysfunction rely heavily on traditional risk factors, such as eGFR, age, and blood pressure, which may not fully capture the complex interplay of various contributory factors.[15–17] In addition, previous studies often focus on specific subgroups (eg, diabetic patients) and certain regions (eg, Western countries), which may limit their generalizability to diverse populations, such as RTRs in China.[15–17]

To address these gaps, this retrospective cohort study aimed to establish a risk prediction model for renal dysfunction among Chinese RTRs based on abnormal lipid profiles using machine learning. We developed a nomogram to visually present the predictive role of lipid abnormality in renal dysfunction. By incorporating specific lipid parameters, the nomogram provides a more nuanced understanding of their roles in renal dysfunction and offers a novel approach to enhance the predictive power of the model. Additionally, combining a nomogram with specific lipid parameters enables personalized risk stratification, allowing for earlier intervention and potentially improving patient outcomes.

Methods

Study Design and Participants

The retrospective cohort study was conducted at Xiangya Hospital of Central South University in Changsha, China, from January 2015 to December 2021. A cohort of 442 patients who underwent kidney transplantation were consecutively recruited and followed up every 3 months till the 12th month after transplantation. We chose a one-year observation period after a renal transplant because it provides a more accurate and stable representation of the patient's post-transplant course, allowing for more complete data collection and better prediction of long-term success.[18] Short-term outcomes are often dominated by immediate surgical and acute factors, resulting in a weaker and less direct correlation between blood lipids and renal dysfunction. Long-term results are confounded by numerous factors, making it challenging to define the independent impact of preoperative blood lipids clearly. Therefore, collecting preoperative blood lipid indicators is essential for predicting the function of a transplanted kidney one year after surgery.

The inclusion criteria were as follows: (1) age $\geq$ 18 years old, (2) the transplanted kidney performed normal functions after a successful kidney transplant, (3) with complete data on key variables such as lipid levels and eGFR, (4) completed one-year follow-up. Patients with the following conditions were excluded: (1) age< 18 years old (n=3), (2) Combined with other organ transplantation or renal re-transplantation (n=5), (3) renal failure due to issues like rejection, infection, or the recurrence of the original kidney disease within 3 months after surgery (n=7), (4) lost to follow-up (n=45), and (5) missing data on preoperative blood lipids (n=37). Finally, 345 patients were included in the analysis. No patients received statins or lipid-lowering medications preoperatively, as it is not required for kidney transplantation.[19]

Figure 1 shows the flowchart of patient enrollment. The research protocol was approved by the Ethics Committee of Xiangya Hospital, Central South University (Protocol No. 202308173). Informed consent was waived due to the retrospective nature of the study. All patient information was collected anonymously and kept confidential.

Data Collection

We collected patients' general information and laboratory test data from their electronic medical records in the hospital health information system. General information included gender, age, marital status, medical payment method, pre-operative comorbidities (diabetes, HBV), family history (hypertension, diabetes), smoking history, drinking history, dialysis method, systolic blood pressure (SBP), and diastolic blood pressure (DBP) at admission. Laboratory test data included preoperative total cholesterol (TC), triglycerides (TG), LDL-C, HDL-C, non-HDL-C, albumin (ALB), and

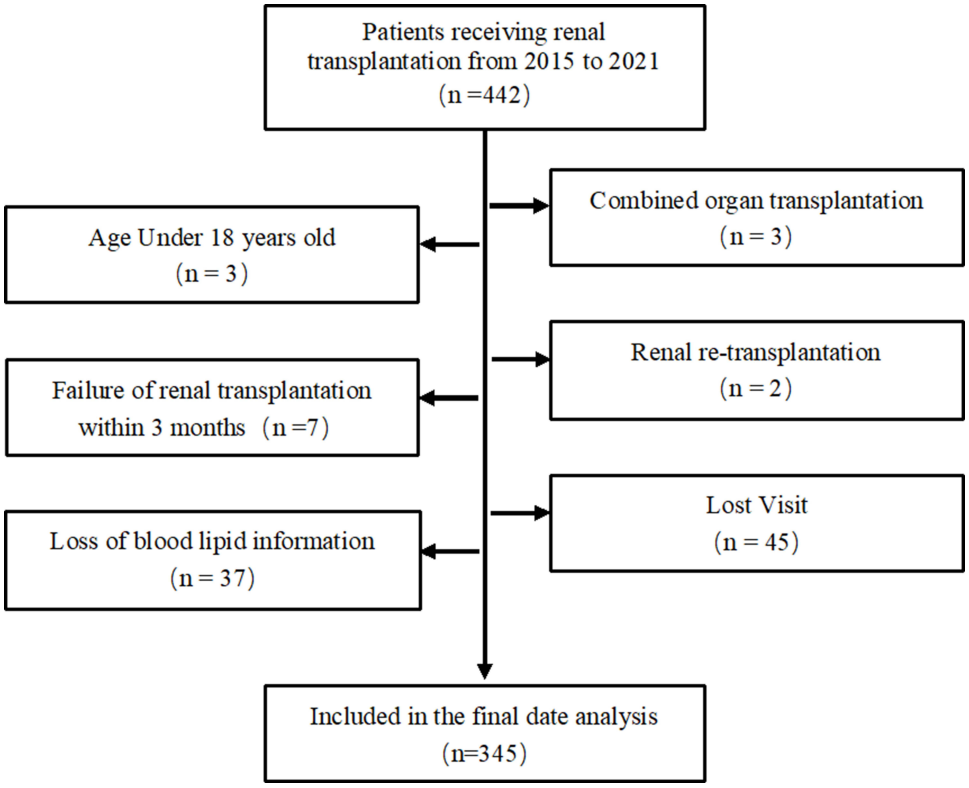

Figure 1 Flow diagram of the study participants.

fasting plasma glucose (FPG), as well as creatinine at 12 months after transplantation. The non-HDL-C value was calculated by subtracting HDL-C from TC.[20] Renal function was assessed by calculating the eGFR based on creatinine levels using the CKD-EPI formula.[21] All patients received postoperative triple immunosuppressive therapy, consisting of glucocorticoids, calcineurin inhibitors, and mycophenolate mofetil. All patients underwent regular postoperative follow-up in accordance with clinical guidelines.

Definition of Key Indicators

According to the 2009 CKD model and previous studies, renal dysfunction was defined as eGFR<60 mL/min / 1.73 m^2.[6,22,23] eGFR was calculated using the CKD-EPI equation developed by the Chronic Nephropathy Epidemiology Collaborative Group in 2009 as follows: $eGFR=141\times\min(Scr/79.6, 1)^{-0.411}\times\max(Scr/79.6, 1)^{-1.209}\times0.993^{Age}$ (Male); $eGFR=141\times\min(Scr/61.9, 1)^{-0.329}\times\max(Scr/61.9, 1)^{-1.209}\times0.993^{Age}\times1.018$ (Female). The median creatinine value, κ, in mg/dL (88.4) was converted to μmol/L. Scr was creatinine, min indicated the minimum of Scr/κ or 1, and max indicated the maximum of Scr/κ or 1.[21] In this study, renal dysfunction was defined as eGFR<60 mL/min /1.73 m^2, dyslipidemia was defined as TC≥5.18mmol/L or TG≥1.7mmol/L or LDL-C≥3.37mmol/L or HDL-C<1.04mmol/L or Non-HDL-C≥4.1mmol/L.[20,24]

Statistical Analysis

Statistical analyses were performed using R (University of Auckland, New Zealand, Version 3.6.2) and SPSS 26.0 (IBM Corp., Armonk, NY, USA). The continuous data were expressed as means ± standard deviations ($\bar{x} \pm s$), and the differences between groups were compared using the Student's *t*-test. Categorical data were expressed as numbers (percentages), and the differences between groups were compared using the χ^2 test. A two-sided $P < 0.05$ was considered statistically significant. The risk prediction model for renal dysfunction was built as follows:

Dataset construction: A total of 345 patients were included in this study, among whom 55.9% had renal dysfunction. To improve the stability of the prediction model, each continuous variable was standardized into a Z-score. After preprocessing the raw data, the patients were randomly assigned to the training set (n=276) and the validation set (n=69)

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in a 4:1 ratio. The training set was used for model selection and hyperparameter adjustment, and the validation set was used to evaluate the final established model.

Predictor screening: predictors of renal dysfunction were screened by calculating the weighted importance of each variable using three standard ML models: RandomForest, XGBoost, and LightGBM. These ML algorithms were selected because they can capture and shape nonlinear relationships between variables without requiring the relationship form to be specified a priori.[25] They can be employed to identify key features and develop prediction models with satisfactory sensitivity and specificity.[25] All three ML models were developed and validated using open-source Python packages (Scikit learn, XGBoost) and LightGBM. A higher importance value indicates a stronger influence of that variable on predicting renal dysfunction. We selected the top ten variables with the highest weighted importance across three models as significant predictors of renal dysfunction. We used correlation tests to screen out the first batch of predictors and retained variables that were significant at $P < 0.05$. This study employed 5-fold cross-validation for model training, dividing the training set into five mutually exclusive parts (four for model training and one for internal validation). This process was repeated five times to generate five different but overlapping training datasets and five independent validation datasets. During the training process, a grid search was employed to optimize the model's hyperparameters, and the area under the curve (AUC) of the receiver operating characteristic (ROC) curve was used as the evaluation criterion for selecting the final model, which was then independently evaluated on the validation set.

A logistic regression model was used to draw an alignment diagram and evaluate the probability of renal dysfunction occurring 12 months after transplantation. To investigate whether there was a significant linear trend in the screening of essential eigenvalues and eGFR at 12 months after surgery, we used trend tests (p for trend) and interaction tests (P for interaction). Variables with a small p for trend ($P<0.05$) indicate a significant linear relationship with renal dysfunction and were thus retained in the final model. A nomogram was plotted with the final selected predictive factors, which provides a more intuitive and transparent visual presentation of statistical models than the "black box" nature of complex ML models like ensembles. In addition, nomograms are designed for practical use in clinical settings, providing a more user-friendly interface that can be readily interpreted than ensembles. Calibration curves were used to assess the accuracy of the prediction model. Decision Curve Analysis (DCA) was used to evaluate the net benefit of the prediction model by visually demonstrating the performance of different strategies in balancing the trade-off between treatment and missed diagnosis.

Results

Sample Characteristics

Table 1 shows the baseline sample characteristics and comparison by renal dysfunction. Among the 345 patients in the cohort, 228 (66.1%) were males and 117 (33.9%) were females, with an average age of 42.0 ± 10.7 (18.0–70.0) years. In

Table 1 Comparison of General Characteristics of Patients with Different Levels of eGFR (n=345)

Variable	eGFR<60 (n=193,%)	eGFR≥60 (n=152,%)	*P* value
Gender			<0.001
Male	108(47.4)	120(52.6)	
Female	85(72.6)	32(27.4)	
Age, year			0.010
18-30	20(38.5)	32(61.5)	
31-45	86(54.1)	73(45.9)	
46-59	77(65.8)	40(34.2)	
≥60	10(58.8)	7(41.2)	

(*Continued*)

Table 1 (Continued).

Variable	eGFR<60 (n=193,%)	eGFR≥60 (n=152,%)	*P* value
Marital status			0.084
Unmarried	20(43.5)	26(56.5)	
Married	168(57.1)	125(42.9)	
Divorced	5(83.3)	1(16.7)	
Medical Payment Method			0.423
At public expense	2(40.0)	3(60.0)	
Municipal medical insurance	43(50.0)	43(50.0)	
Provincial health insurance	15(65.2)	8(34.8)	
Other medical insurance	133(57.6)	98(42.4)	
T2DM			0.550
Yes	16(61.5)	10(38.5)	
No	177(55.5)	142(44.5)	
HBV			0.898
Yes	22(55.0)	18(45.0)	
No	171(56.1)	134(43.9)	
Family history of hypertension			0.070
Yes	24(70.6)	10(29.4)	
No	169(54.3)	142(45.7)	
Family history of diabetes			0.233
Yes	10(71.4)	4(29.6)	
No	183(55.3)	148(44.7)	
Smoking history			0.824
Yes	40(54.8)	33(45.2)	
No	153(56.3)	119(43.7)	
History of drinking			0.641
Yes	21(52.5)	19(47.5)	
No	172(56.4)	133(43.6)	
Dialysis type			0.458
Hemodialysis	145(57.1)	109(42.9)	
Peritoneal dialysis	28(50.9)	27(49.1)	
Both	8(72.7)	3(27.3)	
Neither	12(48.0)	13(52.0)	
TC, mmol/L	5.15±1.32	4.84±1.31	0.028*
TG, mmol/L	2.17±1.20	1.79±1.08	0.002*
HDL-C, mmol/L	1.11±0.41	1.26±0.42	0.001*
LDL-C, mmol/L	3.19±1.07	2.92±0.94	0.014*
Non-HDL-C, mmol/L	4.04±1.17	3.58±1.13	<0.001*
ALB, g/L	42.38±5.60	43.72±5.50	0.026*
FPG, mmol/L, median	6.56±2.94	5.98±1.92	0.037*
SBP, mmHg			
≥140	149 (56.0)	117 (44.0)	0.960
<140	44 (55.7)	35 (44.3)	
DBP, mmHg			0.292
≥90	115 (53.7)	99 (46.3)	
<90	78 (59.5)	53 (40.5)	

Notes: The *P* value was calculated by the Chi-square test. *The *P* value was calculated by the Student's *t*-test.

Abbreviations: TC, total cholesterol; TG, triglyceride; HDL-C, high-density lipoprotein cholesterol; LDL-C, low-density lipoprotein cholesterol; non-HDL-C, non-highdensity lipoprotein cholesterol; ALB, Albumin; FPG, fasting plasma glucose; T2DM, diabetes mellitus type 2.

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addition, 26 (7.5%) patients had diabetes, 40 (11.6%) had HBV, 34 (9.9%) had a family history of hypertension, 14 (4.1%) had a family history of diabetes, 73 (21.2%) had a smoking history, 40 (11.6%) had an alcohol use history. Most patients received dialysis treatment before transplantation (92.8%). The prevalence of preoperative abnormalities in TC, TG, LDL-C, HDL-C, and non-HDL-C was 136 (39.4%), 183 (53.0%), 111 (32.2%), 146 (42.3%), and 122 (35.4%), respectively. No significant differences were observed in the sample characteristics between the training and validation sets.

At the 12-month follow-up, the cohort had a mean eGFR of 57.14±19.61 mL/min/1.73 m², with 193 (55.9%) patients exhibiting renal dysfunction with an eGFR abnormality. Comparison of baseline characteristics between patients with and without renal dysfunction showed significant differences in the following nine variables: gender, age, TC, TG, LDL-C, non-HDL-C, FPG, HDL-C, and ALB. Specifically, patients with renal dysfunction were more likely to be female, aged<60, and had higher levels of TC, TG, LDL-C, non-HDL-C, and FPG, as well as lower levels of HDL-C and ALB (Table 1).

Screening of Candidate Predictors

All baseline sample characteristics (20 variables) were selected as candidate predictors as the input, and renal dysfunction was set as the outcome in the training set and validation set. We used Random Forest, XGBoost, and LightGBM to calculate the feature importance (Table S1), weighted feature importance (Table S2), and Pearson values (Table S3). We selected the top 10 variables with the highest weighted importance as well as significant correlation coefficients. Based on importance and correlation p-value, the following nine variables were selected: preoperative TC (weighted importance: 0.070; r=0.12, P=0.028), TG (weighted importance: 0.097; r=0.16, P=0.002), LDL-C (weighted importance: 0.053; r=0.13, P=0.014), HDL-C (weighted importance: 0.064; r=0.17, P=0.001), non-HDL-C (weighted importance: 0.084; r=0.20, P<0.001), ALB (weighted importance: 0.066; r=0.12, P=0.026), FPG (weighted importance: 0.072; r=0.11, P=0.037), gender (weighted importance: 0.058; r=0.24, P<0.001), and age (weighted importance: 0.081; r=0.20, P<0.001) (Tables S2 and S3). HDL-C (r=−3.26), non-HDL-C (r=1.80), gender (r=−1.15), and age (r=1.53) showed a high coefficient in the SVM model (Table 2).

Establishment of the Risk Prediction Model

We found low correlations for the nine variables and performed trend testing for each variable, which identified three suitable variables showing a linear trend with renal dysfunction: non-HDL-C (p-trend = 0.0002), HDL-C (p-trend = 0.008), and LDL-C (p-trend = 0.036) (Tables S4 and S5). Higher non-HDL-C, higher LDL-C, and lower HDL-C were associated with a higher risk of renal dysfunction. HDL and non-HDL showed no interaction (P=0.257)(Table S6). In contrast, TC, TG, FPG, and ALB showed no apparent trend.

Table 2 Results of Gaussian Linear Model Fitting

	Coef
preHDL-C	−3.260845
Prenon-HDL-C	1.800374
Age	1.528826
Gender	−1.153818
preALB	−0.932429
preTG	0.885750
preFPG	0.532901
preTC	0.525701
preLDL-C	−0.182000

Abbreviation: coef, coefficient in SVM model.

Therefore, the final predictive model was constructed based on five preoperative variables: non-HDL-C, HDL-C, LDL-C, age, and gender, with the ROC curves plotted. The AUC of the three models in the training set were 1.00 (95% CI:1.00, 1.00), 0.93 (95% CI: 0.91, 0.95), and 1.00 (95% CI:1.00, 1.00), respectively, and in the validation set were 0.80 (95% CI:0.79, 0.83), 0.75 (95% CI: 0.72, 0.77), and 0.80 (95% CI:0.78, 0.81), respectively (Figure S1).

Evaluating the Diagnosis Performance of the Model

A nomogram was plotted using the final five selected predictive factors, as determined by logistic regression, to predict the individualized risk of renal dysfunction among RTRs after transplantation, as shown in Figure 2. Each indicator corresponds to a point score by drawing a vertical line above the value point of each indicator axis, which intersects with the point axis to get a point score. The total score is the sum of all eight indicator scores. It corresponds to the risk of renal dysfunction, which is determined by drawing a vertical line below the total score on the total point axis to intersect with the risk probability axis, thereby obtaining the risk probability. The nomogram indicated that older age, female gender, lower preoperative HDL-C levels, higher preoperative non-HDL-C levels, and higher preoperative LDL-C levels were associated with a higher risk of renal dysfunction (Figure 2). The nomogram demonstrated good diagnostic performance, with an area under the curve (AUC) of 0.87 (95% CI: 0.82, 0.92) in the training group and 0.81 (95% CI: 0.72, 0.87) in the validation group (Figure S2), which was consistent with the calibration results (Figure S3).

DCA was employed to assess the clinical utility of the diagnostic nomogram, which demonstrated sufficient robustness in both the training and validation sets. Moreover, a threshold probability of 0.56 provided the most benefits in predicting potential patients with renal dysfunction (Figure 3A). The model's clinical utility was further evaluated using the clinical impact curve (CIC), with a threshold probability of 0.78 demonstrating the best predictive performance (Figure 3B).

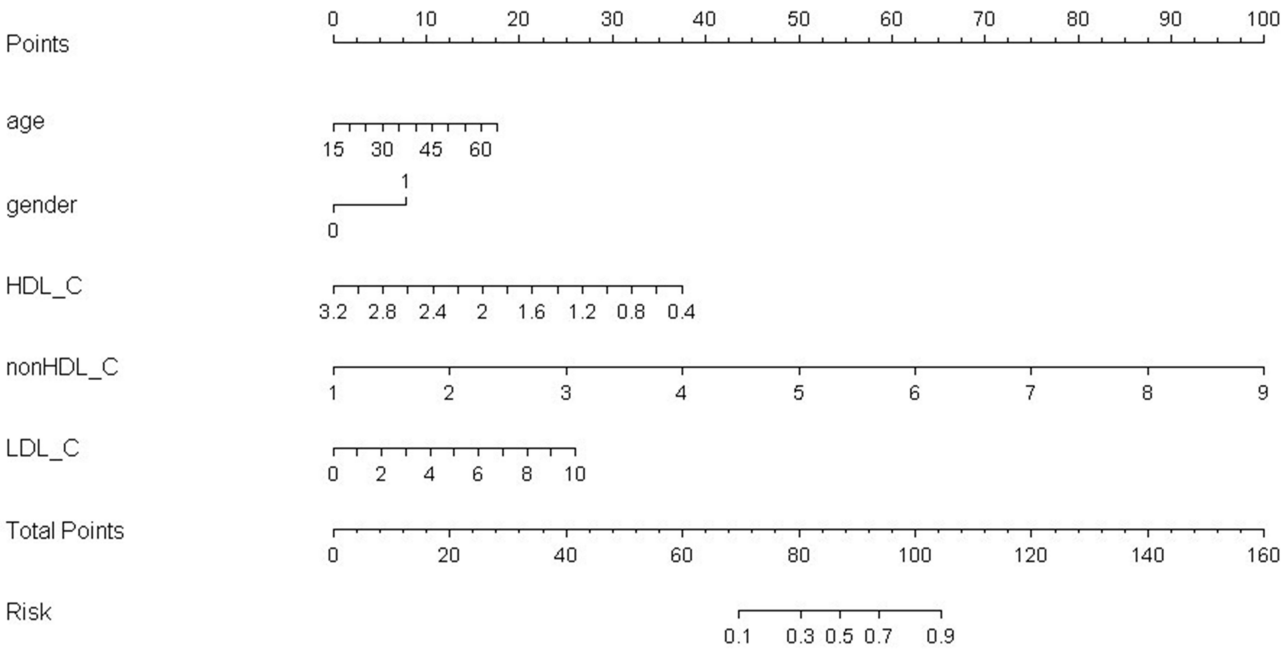

Figure 2 Nomogram for identifying eGFR abnormalities. The value of each variable was scored on a point scale from 0 to 100, after which the scores for each variable were added together. That sum is located on the total points axis, which enables us to predict the probability of eGFR abnormality risk. For gender categories, 0= male, 1= female.

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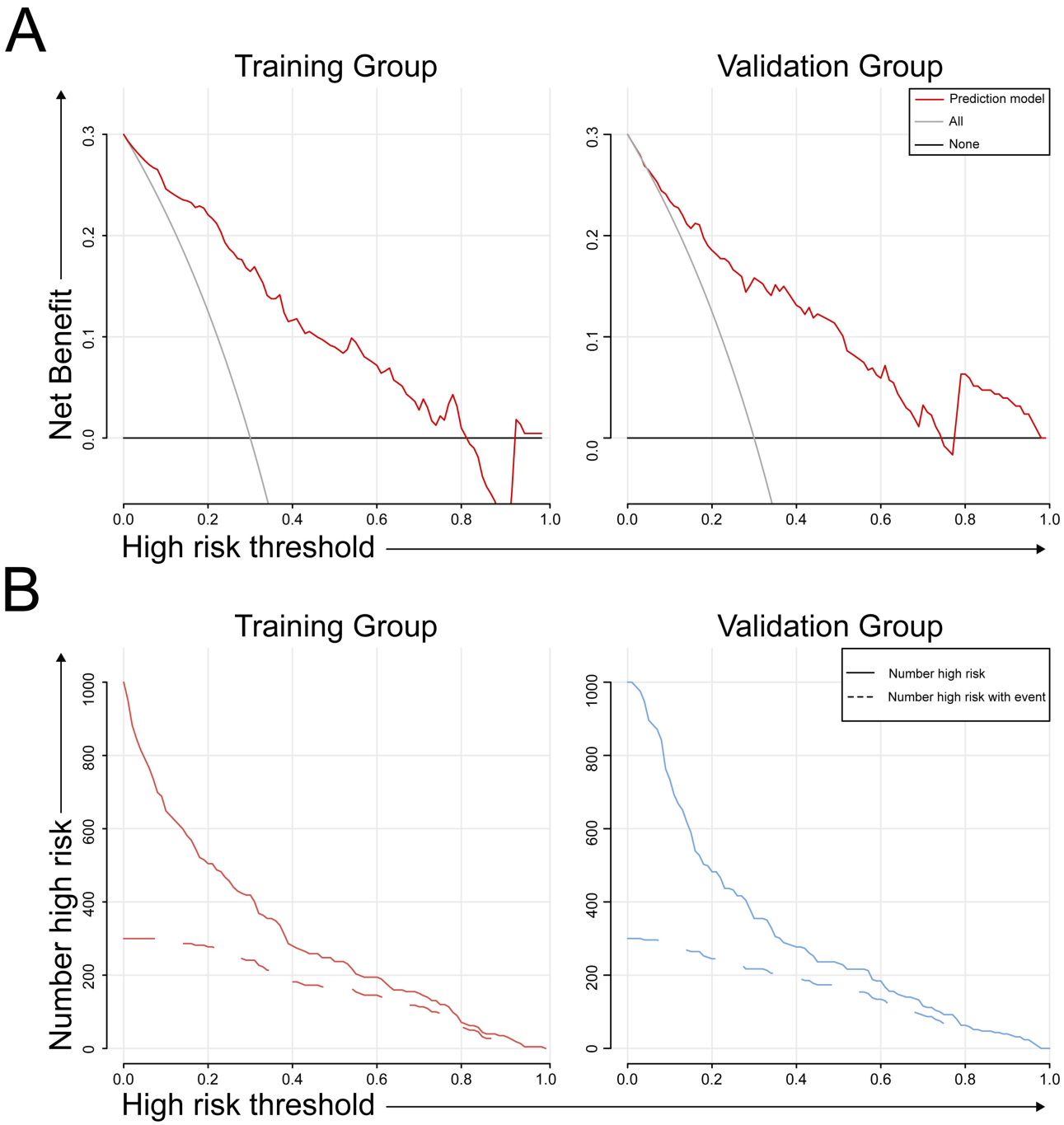

Figure 3 The clinical value of the prediction model for renal function. (**A**) Decision curves. The y-axis denotes the net benefit. Red line: the prediction model; Grey line: all recipients had eGFR abnormalities (assumption); Black line: non-recipients had eGFR abnormalities (assumption). (**B**) Clinical impact curves. Solid line: people judged as high risk; Dotted line: people judged as high risk and actually experienced an outcome event.

Discussion

Summary of the Findings

In this retrospective cohort study, we used three ML methods to explore the predictive effects of preoperative lipid profiles on postoperative renal dysfunction among RTRs. Our results showed that older age, female gender, lower preoperative HDL-C, higher preoperative non-HDL-C, and higher preoperative LDL-C were associated with a higher

risk of renal dysfunction. We further established a nomogram based on the five predictors, which showed good diagnostic performance and clinical utility in both the training set and the validation set.

Prevalence of Key Variables

In our study, more than half of RTRs experienced renal dysfunction with eGFR abnormality at 12 months of follow-up. In addition, the prevalence of abnormal HDL-C, non-HDL-C, and LDL-C was 42.3%, 35.4%, and 32.2%, respectively, which were highly correlated with postoperative renal dysfunction. Although kidney transplantation has improved the long-term outcomes of patients with end-stage renal disease, postoperative renal dysfunction remains a considerable challenge. Our findings suggest that before kidney transplantation, the risk of renal dysfunction should be carefully evaluated, and evidence-based intervention strategies should be established, including routine screening of non-HDL-C, HDL-C, and LDL-C levels, the rational use of lipid-lowering drugs, and lifestyle interventions.

Predictors of Renal Dysfunction

Our study showed that lower preoperative HDL-C was associated with a higher risk of postoperative renal dysfunction, which is consistent with the results of a large cross-sectional study based on 4753 older adults.[26] The mechanism by which low HDL-C impairs renal function has not been fully elucidated. HDL-C is a highly heterogeneous particle that carries various substances, including lipids, proteins, hormones, etc. It enhances the reverse transport of cholesterol in macrophages, promotes the production of nitric oxide (NO) by endothelial cells (ECs), and has antioxidant, anti-inflammatory, and anti-apoptotic properties. Low HDL-C levels may impair these properties and lead to renal damage.[27,28] Therefore, it is suggested that controlling HDL-C at a normal level before kidney transplantation may be beneficial for preventing postoperative renal dysfunction and prolonging graft survival.

In addition, our study showed that higher preoperative non-HDL-C was associated with a higher risk of postoperative renal dysfunction. Non-HDL-C refers to the total cholesterol in ApoB lipoprotein particles in the blood after excluding HDL-C, which has a potential atherogenic effect. High levels of non-HDL-C lead to the accumulation of arterial plaque, thus increasing the risk of CVD.[9] Although there is no conclusive evidence on the mechanism of non-HDL-C affecting renal function, high levels of non-HDL-C may promote the progression of renal dysfunction by increasing the risk of CVD. A prospective cohort study evaluating 3909 participants found a significant correlation between non-HDL-C levels and early progression of renal injury.[29] Furthermore, high TC or low HDL-C levels may cause high non-HDL-C, and the accumulation of cholesterol cells can lead to lipotoxicity, ultimately causing renal dysfunction.[30] The damage caused by high preoperative non-HDL-C on renal function may be attributed to lipid toxicity-induced arterial plaque accumulation or high TC levels associated with inhibition of renal tubular epithelial cell proliferation.[31]

Furthermore, this study found that higher preoperative LDL-C levels were associated with a higher risk of post-operative renal dysfunction. However, they did not contribute as much as non-HDL-C and HDL-C. Our finding was consistent with Tsai et al's[32] prospective cohort study of 46278 community participants, which found that eGFR showed a significant downward trend with increasing LDL-C levels. Higher preoperative LDL-C indicates the loss of antioxidants and the accumulation of oxidative products, which can lead to excessive oxidative stress and oxidation of LDL in the arterial wall, thus accelerating the deterioration of renal function.[33,34] Studies showed that patients with low LDL-C had better renal prognosis than those with high LDL-C.[35] Routine postoperative screening and postoperative monitoring of LDL-C levels are highly recommended for RTRs. Patients with high levels of LDL-C should be given statin therapy and adopt a healthy lifestyle to control LDL-C at the target level to prevent renal dysfunction.

Advantages and Limitations

Our study has several advantages. First, the model was developed based on a Chinese sample of RTRs, ensuring its cultural adaptability within the Chinese context while also enabling global comparisons. By understanding the model's performance in a Chinese population, researchers can identify both the unique characteristics and universal elements that might apply to other cultures or necessitate further adaptation for a global context. Second, while existing prediction models for renal dysfunction primarily rely on traditional risk factors, such as eGFR and blood pressure, our model innovatively focused on the role of lipids, a less-studied yet equally important area. By examining the interaction

between various lipids and their influence on kidney function, the model may lead to more accurate predictions and a deeper understanding of the mechanisms underlying renal dysfunction. Third, the model is based on standard indicators that are readily obtainable from preoperative blood testing in clinical practice, ensuring simplicity, practicality, efficiency, and cost-effectiveness. Evaluation of preoperative lipid profiles can predict the function of allografts, thus benefiting RTRs.

However, our study also has several limitations. First, our study employed a retrospective design, and all data were retrieved from medical records, which may have led to bias and missing information. For instance, drugs that may affect lipid profiles, dietary guidance RTRs received peri- and post-transplantation, and dialysis vintage are all critical potential confounders that may affect both lipid profiles and renal dysfunction. However, data on these variables were not available from the medical records. Future studies should prospectively collect these variables to get a more comprehensive and robust evaluation. Second, RTRs generally require lifelong immunosuppressive therapy to prevent their immune system from attacking and rejecting the transplanted organ. These drugs, while critical for transplant survival, constitute an essential confounder as they may exert varying degrees of influence on lipid metabolism and renal function in RTRs. Third, the one-year follow-up period was relatively short and may not reflect the long-term changes in the association between lipid profiles and renal dysfunction. Fourth, the small sample size may compromise the model's stability. Future studies should consider using larger sample sizes, longer follow-up durations, and trajectory analysis methods to test our model and analyze the impact of lipid profiles on renal dysfunction among RTRs. Fifth, abnormal blood lipids in our study were defined based on the Chinese guidelines instead of international guidelines, which may limit global comparison. However, using local guidelines better aligns with the healthcare research and practice in a Chinese context. Future research should balance the benefits of international best practices with the need for local applicability. Finally, we did not collect information on albuminuria and determined renal dysfunction using the 2009 CKD model based on one indicator, eGFR. Although this dichotomous classification is relatively efficient and easy to use, it cannot distinguish patients with different levels of renal dysfunction, such as low, moderate, high, and very high levels. Future studies may consider adopting the latest Kidney Disease: Improving Global Outcomes (KDIGO) 2012 guidelines to classify patients into various levels of renal dysfunction based on the combined assessment of eGFR and albuminuria status.

Implications

The nomogram has significant clinical implications to be widely applied in clinical practice to predict renal dysfunction in RTRs. Clinicians can use the nomogram score to categorize patients into different risk groups (eg, low, intermediate, high) for renal dysfunction and adjust the intensity of follow-up based on this categorization. For example, high-risk patients might require more frequent monitoring, stricter screening protocols, or early intervention strategies compared to low-risk individuals. In addition, nomograms provide a visual and numerical representation of a patient's individual risk for renal dysfunction, which can help clinicians and patients make transparent and informed decisions about treatment strategies, including medication choices.

Conclusion

This study indicated that age, gender, and preoperative levels of non-HDL-C, HDL-C, and LDL-C were independent predictors of postoperative renal dysfunction in RTRs. Furthermore, we constructed a nomogram composed of the five factors, which showed good predictive performance. This model suggests the potential for identifying RTRs at high risk of renal dysfunction and providing a clinical decision-making basis for promoting the rational use of lipid-lowering drugs and personalized lifestyle interventions. Future studies, including independent external validation, are essential to establish the model's reliability and widespread utility.

Data Sharing Statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Ethical Approval and Consent to Participate

The study involving human participants was reviewed and approved by the Ethics Committee of Xiangya Hospital, Central South University (registration number: 202308173). All kidneys were donated voluntarily with written informed consent, and that this was conducted in accordance with the Declaration of Istanbul.[36] All the procedures were followed in accordance with the Declaration of Helsinki.[37] Each participant was informed of the purpose of the study and signed a written informed consent.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors report no conflicts of interest in this work.

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