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Development and validation of a nomogram for predicting low Kt/V_{urea} in peritoneal dialysis patients

Danfeng Zhang[1,2,3†], Tian Zhao[3†], Liting Gao[1,2], Huan Zhu[4], Haowei Jin[4], Guiling Liu[1,2*] and Deguang Wang[1,2*]

Abstract

Background This study aimed to develop a nomogram to predict peritoneal dialysis (PD) adequacy in incident PD patients and identify those at high risk for low Kt/Vurea PD function.

Methods We retrospectively analyzed 141 incident PD patients from January 2021 to January 2024. Baseline characteristics, including BMI, hemoglobin levels, and high transport PD membrane, were compared between patients with and without adequate PD function. Univariate logistic regression, LASSO analysis, and Random Forest (RF) algorithms were employed to identify potential biomarkers. Significant predictors were integrated into a multivariable logistic regression model to construct a predictive nomogram.

Results The study found that 32.1% of patients had low total Kt/Vurea. Significant predictors of low Kt/Vurea included smoking (OR 2.23, CI 1.47–5.85), BMI (OR 1.35, CI 1.17–1.59), hemoglobin levels (OR 0.98, CI 0.95–0.99), and High transport (OR 0.2., CI 0.04–0.72). These factors were incorporated into a nomogram, which demonstrated strong predictive accuracy, with a C-Index of 0.802 in the main study group. The model's AUC was 0.778 (95% CI: 0.686–0.870), and Decision Curve Analysis (DCA) confirmed its clinical utility across a wide range of threshold probabilities.

Conclusions We developed a nomogram that accurately predicts PD total Kt/Vurea in incident PD patients. This model can be a valuable tool for identifying patients at risk of low PD total Kt/Vurea, facilitating timely interventions to improve patient outcomes.

Keywords Peritoneal dialysis, Kt/Vurea, LASSO, Nomogram

†Danfeng Zhang and Tian Zhao contributed equally to this work.

Recall international standards which contribution qualifies for authorship.

*Correspondence:
Guiling Liu
guilingliu369@163.com
Deguang Wang
wangdeguang@ahmu.edu.cn

[1]Department of Nephrology, The Second Affiliated Hospital of Anhui Medical University, Hefei, China
[2]Institute of Kidney Disease, Inflammation & Immunity-mediated Diseases, The Second Affiliated Hospital of Anhui Medical University, Hefei, China
[3]Inflammation and Immune Mediated Diseases Laboratory of Anhui Province, The Key Laboratory of Anti-inflammatory of Immune Medicines, Ministry of Education, Anhui Institute of Innovative Drugs, School of Pharmacy, Anhui Medical University, Hefei, China
[4]Second School of Clinical Medicine, Anhui Medical University, Hefei, China

Introduction

Kidney failure is a global health issue that imposes a substantial burden on individuals and society. Peritoneal dialysis (PD) and hemodialysis are the primary therapeutic options for kidney failure. Peritoneal dialysis is increasingly preferred by many patients since it may be done at home and has a less disruptive impact on their daily routines [1, 2]. In addition, by utilizing the peritoneum as a dialysis membrane, peritoneal dialysis removes toxins and excess water from the body in a continuous and gentle manner, helping to protect the patient's residual kidney function (RKF), which is essential for maintaining the patient's long-term health [3].

Despite the controversy surrounding its use, it is generally accepted that the Kt/V value is an important parameter reflecting the effectiveness of dialysis, and it is closely related to the prognosis of patients [4]. The adequacy of peritoneal dialysis is influenced by a variety of factors, including the composition of the dialysate, the individualization of the dialysis regimen, the nutritional status of the patient, hyperinflammatory states, and residual kidney fuction [5, 6].

Nomogram as a predictive tool provides an intuitive, personalized means of risk assessment and decision support by integrating multiple clinically relevant variables [7, 8]. In the field of peritoneal dialysis, nomogram has been used to predict clinical outcomes in dialysis patients, including PD associated peritonitis, survival, hospitalization, and risk of technical failure [9–11]. However,the modeling of the dialysis adequacy of small molecule solutes for peritoneal dialysis has not yet been established. Additionally, the current assessment of dialysis adequacy for small molecule solutes is based on urea clearance, which is time-consuming and requires patients to collect 24 hours of urine and 24 hours of peritoneal dialysate [12, 13]. Furthermore, it is challenging to ensure the collection of urine specimens in a standardized manner in less affluent regions and among older adults and individuals residing in remote areas [14, 15]. The development of a predictive model for small molecule solute dialysis adequacy in PD patients based on serum biomarkers would markedly enhance the convenience of conducting clinical dialysis adequacy assessments and reduce the economic burden of disease. This model represents a departure from traditional methods, offering a more patient-friendly and cost-effective solution that has the potential to transform clinical practice in the management of PD patients.

The objective of this study is to develop a serologic risk prediction model based on a collection of simple and readily available biological indicators to enhance the simplicity of dialysis adequacy assessment in peritoneal dialysis patients.

Methods

Study design and population

This study includes 141 CAPD patients aged > 18 years with ESRD receiving CAPD for at least 3 months from the Second Hospital of Anhui Medical University between January 2022 and January 2024. All patients were administered standard lactated peritoneal dialysis solution containing 1.5% and 2.5% glucose. The exclusion criteria were (1)the onset of PD for other reasons, such as acute kidney injury or acute kidney failure; (2) congestive heart failure, malignant tumor, liver failure, and severe infection; (3) patients received kidney transplant or HD before the onset of PD.

All participants submitted written expressions of consent. This study adhered to the Declaration of Helsinki and was approved by the Ethics Committee of The Second Hospital of Anhui Medical University (YX2022-014).

Clinical covariates

Clinical and laboratory data were collected using standardized forms. Following variables were considered: the demographic variables, including age, sex, and smoking status; physical examination variables, including systolic blood pressure (SBP) and diastolic blood pressure (DBP), heart rate, body weight with dry abdomen and height. The body mass index was calculated according to weight and height. A history of cardiovascular events (CVEs) was recorded, which was defined as a history of coronary heart disease, heart failure, stroke, andperipheral arterial disease. Laboratory data, including neutrophil/lymphocyte,hemoglobin, c-reactive protein (CRP), calcium,phosphorus, serum uric acid, creatinine, blood urea nitrogen (BUN), albumin, cholesterol, triglycerides and intact parathyroid hormone (iPTH).

kidney Kt/V assesses residual kidney function by calculating the clearance of urea from the body, based on residual kidney clearance and total body water. The total Kt/V combines both kidney and peritoneal clearances to provide an overall measure of dialysis adequacy. The peritoneal Kt/V is calculated as the ratio of urea clearance via the peritoneal membrane to the total body water (TBW). Urea clearance during a standard peritoneal dialysis exchange is estimated by the following formula:

$$Kt/V_{\text{peritoneal}} = \frac{(C_{out} - C_{in}) \times V_{in}}{TBW}$$

Where C_{out} and C_{in} are the urea concentrations in the effluent dialysate after and before the exchange, respectively; V_{in} is the volume of dialysate infused into the peritoneal cavity; TBW is the total body water, which is typically estimated using bioimpedance analysis or other clinical methods.

The kidney Kt/V reflects the clearance of urea by the residual kidney function. It is calculated based on the 24-hour urinary urea collection or serum urea kinetics over a set period, and is influenced by the patient's urine output and the frequency of dialysis exchanges. The kidney contribution is typically expressed as:

$$Kt/V_{kidney} = \frac{U_{24h} \times C_{urea}}{TBW}$$

where U_{24} represents the total 24-hour urine volume and C_{urea} is the urea concentration in the serum or in the 24-hour urine.

The total Kt/V combines both the kidney and peritoneal contributions

The Peritoneal Equilibration Test (PET) involves a 4-hour peritoneal dialysis exchange using a standard dialysate volume. The dialysate is sampled at various time points (typically 0, 2, and 4 hours), and the concentrations of urea in both the dialysate and plasma are measured. PET classifies patients as high, high average, low, or low average transporters.

Statistical analysis

The National Kidney Foundation – Kidney Disease Outcomes Quality Initiative (NKF KDOQI) PD adequacy guideline stipulates that in patients with residual kidney function, the minimum total Kt/V dose should be at least 1.7 per week. The patients were divided into two groups based on their Kt/V values: the high Kt/V group (defined as ≥ 1.7) and the low Kt/V group (defined as < 1.7).Quantitative data with a normal distribution were presented as mean and standard deviation (SD), whereas skewed data were summarized using the median (M) along with the interquartile range (1/4, 3/4). For categorical data, frequencies and percentages were utilized. Group differences were analyzed using the Chi-square test or Fisher's exact test, as appropriate. For normally distributed variables, comparisons between groups were performed using the t-test. For variables with asymmetrical distributions, the Mann-Whitney U test was employed for group comparisons.

To identify potential biomarkers, we employed univariate logistic regression, LASSO, and random forest (RF) algorithms. In the univariate logistic regression, variables with *P*-values less than 0.05 were considered potential biomarkers. For the LASSO analysis, the full dataset was utilized to develop the model, with cross-validation applied to select the optimal tuning parameter (lambda). Specifically, 10-fold cross-validation was used, dividing the dataset into 10 subsets. The LASSO model was iteratively applied to each fold, choosing the lambda based on the minimum cross-validated error. For the RF algorithms, 10-fold cross-validation was also conducted, selecting the optimal hyperparameters (ntree, mtry, and nodesize). The top five variables with the highest importance scores were identified as potential biomarkers. For multivariable analysis, we combined the potential biomarkers identified by univariate logistic regression, LASSO analysis, and random forest algorithms. The final logistic regression model was selected using backward stepwise regression. Collinearity among the variables in the final model was assessed using the variance inflation factor (VIF), with VIF values ≤ 5 indicating no significant collinearity. Nomograms were created using the 'rms' package in R software, based on the results of the multivariable logistic regression. Internal validation was performed using the bootstrapping method with 1000 resamples. The model's discriminatory power was evaluated using the concordance index (C-Index) to reduce the risk of overfitting. To compare the predictive accuracy of our model with the three biomarkers (BMI and PD duration), we used the area under the curve (AUC). Decision curve analysis (DCA) was employed to assess the clinical utility of the model. All statistical analyses were conducted using R software (version 4.4.0), with *P*-values < 0.05 considered statistically significant.

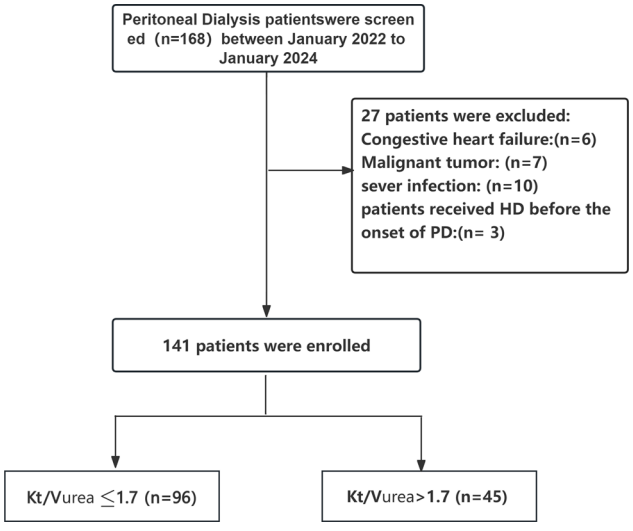

Fig. 1 Flow chart. Kt/Vurea: urea clearance index

Result

Basic characteristics of study subjects

Between January 2021 and January 2024, a total of 168 patients were initially enrolled in the study. Following the application of predefined exclusion criteria, 27 patients were excluded, leaving a final cohort of 141 patients. Of these, 45 patients (32.1%) had low Kt/Vurea values, while 96 patients (67.9%) exhibited high Kt/Vurea values (Fig. 1). The percentage of male of the group with low PD Kt/Vurea was 47.7%, which is 8.2% higher than the group with high Kt/Vurea PD group, of which the percentage

was 39.5%. BMI is significantly higher in low PD Kt/Vurea group than that of high Kt/Vurea PD group. Similarly, PD patients with no adequacy has longer PD vintage than that of individual with adequacy. Significant differences were found between the two groups in terms of BMI, urine output, peritonitis history, CRP, NLR, Hemoglobin, phosphorus,creatinine, ferritin, High transport PD memebrane and PD duration ($p < 0.05$). Table 1 summarizes the basic characteristics of the dataset.

Table 1 Baseline characteristics

Variables	High Kt/V_{urea} (n = 96)	Low Kt/V_{urea} (n = 45)	*P* value
Age (years)	51.3 ± 13.4	53.1 ± 12.8	0.463
Gender,male	34 (39.5)	21 (47.7)	0.48
BMI	21.44 ± 3.28	23.98 ± 3.72	<0.001*
Total K/tv	2 (1.8,2.2)	1.49 (1.5,1.6)	<0.001*
PD K/tv	1.8 (1.5,2)	1.5 (1.3,1.6)	<0.005*
kidney K/tv	0.1 (0,0.5)	0 (0,0.1)	0.014*
SBP(mmHg)	139.85 ± 23.91	139.98 ± 25.21	0.977
DBP (mmHg)	84.43 ± 17.26)	87.34 ± 16.20)	0.355
Heart Rate	80 (76,84)	80 (76,86.5)	0.202
Urine output, n (%)	39 (45.3%)	11 (25.0%)	0.039*
Smoke, n (%)	3 (3.5)	6 (13.6)	0.073
Hypertension, n (%)	72 (83.7)	38 (86.4)	0.890
Diabetes, n (%)	19 (22.1)	15 (34.1)	0.207
Cardiovascular disease, n (%)	10 (11.6)	8 (18.2)	0.450
Peritonitis history			
≥ 2	1(1.04%)	2(4.44%)	<0.001*
1 time	11(11.46%)	9(20%)	0.006
CRP (mg/L)	2.8 (0.8,6.8)	4.8 (2.3,9.1)	0.072
NLR	3.5 (1.2,7.1)	4.9 (2.5,8.7)	0.048*
Hemoglobin (g/L)	100.85 ± 21.54	92.09 ± 16.40	0.018*
Calcium (mmol/L)	2.2 (2.1,2.3)	2.1 (2,2.2)	0.802
Phosphorus (mmol/L)	1.44 ± 0.50	1.69 ± 0.60	0.011*
Creatinine (μmol/L)	715.47 ± 290.90	892.48 ± 388.77	0.004*
BUN (mmol/L)	16.10 ± 5.13	17.86 ± 6.99	0.104
Albumin (g/L)	31.63 ± 4.74	32.54 ± 4.93	0.309
Cholesterol (mmol/L)	4.3 (3.4,4.9)	4.2 (3.5,5)	0.476
HDL(mmol/L)	1.19 ± 0.38	0.99 (0.21)	0.478
LDL(mmol/L)	2.6 (2.2,3.1)	2.7 (2.1,3.2)	0.533
Triglycerides (mmol/L)	1.3 (0.9,1.8)	1.5 (1.1,2.4)	0.082
iPTH (pg/ml)	150.5 (68.1,292)	214 (104,380)	0.339
PD duration(year)	2.2 (1,4)	3 (1.9,5.1)	0.023*
ALP (mmol/L)	93 (71,124.8)	98.5 (80.2,114.8)	0.688
Ferritin(μg/L)	107 (51.8,216.8)	171.5 (82.8,299.2)	0.037*
Transferrin(g/L)	21.2 (12,31)	22.7 (15.3,29.7)	0.875
PD membrane statue			
Low (%)	16 (18.6)	14 (31.8)	0.141
Low average (%)	30 (34.9)	20 (45.5)	0.326
High (%)	24 (27.9)	5 (11.4)	0.055*
High average (%)	16 (18.6)	5 (11.4)	0.418

Abbreviations: Kt/Vurea: urea clearance index; BMI: body mass index; NLR: Neutrophil-to-Lymphocyte Ratio, CRP: c-reactive protein, WBC: white blood cell, BUN: blood urea nitrogen, iPTH, intact parathyroid hormone, PD: peritoneal dialysis, ALP: Alkaline Phosphatase; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure; *: $p < 0.05$

Screening for potential biomarkers

Univariate logistic analysis, LASSO analysis, and RF algorithms were applied to screen potential biomarkers respectively. For the univariate logistic analysis, the incidence of low PD Kt/Vurea group was associated with the BMI (0 R 1.30; 95% CI 1.13–1.51), urine output (OR 0.40; 95% CI 0.18–0.90),smoke (OR 4.368; 95% CI 1.037–18.403), NLR (OR 1.103; 95% CI 1.009–1.205), hemoglobin (OR 0.978; 95% CI 0.959–0.997), phosphorus (OR 2.441; 95% CI 1.197–4.978), PD duration (OR 1.213; 95% CI 1.029–1.429), High transport (OR 0.2; 95% CI 0.046–0.722).In the LASSO analysis, Fig. 2A presents a regression coefficient plot for the model, with each curve representing a distinct variable. At various input levels, the factors with nonzero coefficients and their corresponding values form the LASSO model. Figure 2B illustrates the LASSO feature selection process. To refine the model, 10-fold cross-validation was employed, identifying $\lambda = 0.2$ as yielding the lowest cross-validation error. The resulting LASSO regression model incorporates five potential biomarkers: Hemoglobin, PD duration,BMI, creatinine and high transport. Regarding the Random Forest (RF) algorithms, Fig. 2C displays the ranking of variable importance within the RF model. The RF algorithms identified five potential biomarkers: creatinine, BMI, phosphorus (P), hemoglobin (HB) and PD duartion.

Multivariable logistic regression analysis

The concatenation of potential biomarkers identified through univariate logistic analysis, LASSO analysis, and the RF algorithm was incorporated into a multivariable analysis. To ascertain the most accurate predictors of low PD total Kt/Vurea in CAPD patients, backward stepwise regression was applied within a multivariable logistic regression framework. The multivariable logistic model's mean VIF of 1.17 indicates an absence of multicollinearity among the variables. The multivariable logistic regression identified smoke (OR 2.23, CI 1.47–5.85; p 0.03), BMI (OR 1.30, CI 1.13–1.51; $p < 0.01$) and hemoglobin (OR 0.97, CI 0.94–0.99; $p < 0.01$) and high transport (OR 0.20, CI 0.04–0.722; p 0.02) as significant risk factors for low total Kt/V (Table 2).

Construction of nomogram

The nomogram was developed using the significant predictors from our multivariable analysis, with scores assigned to each variable according to their regression coefficients (Fig. 3). Patients who are smokers, have a higher BMI, lower hemoglobin levels and high transporter are more likely to experience low PD total

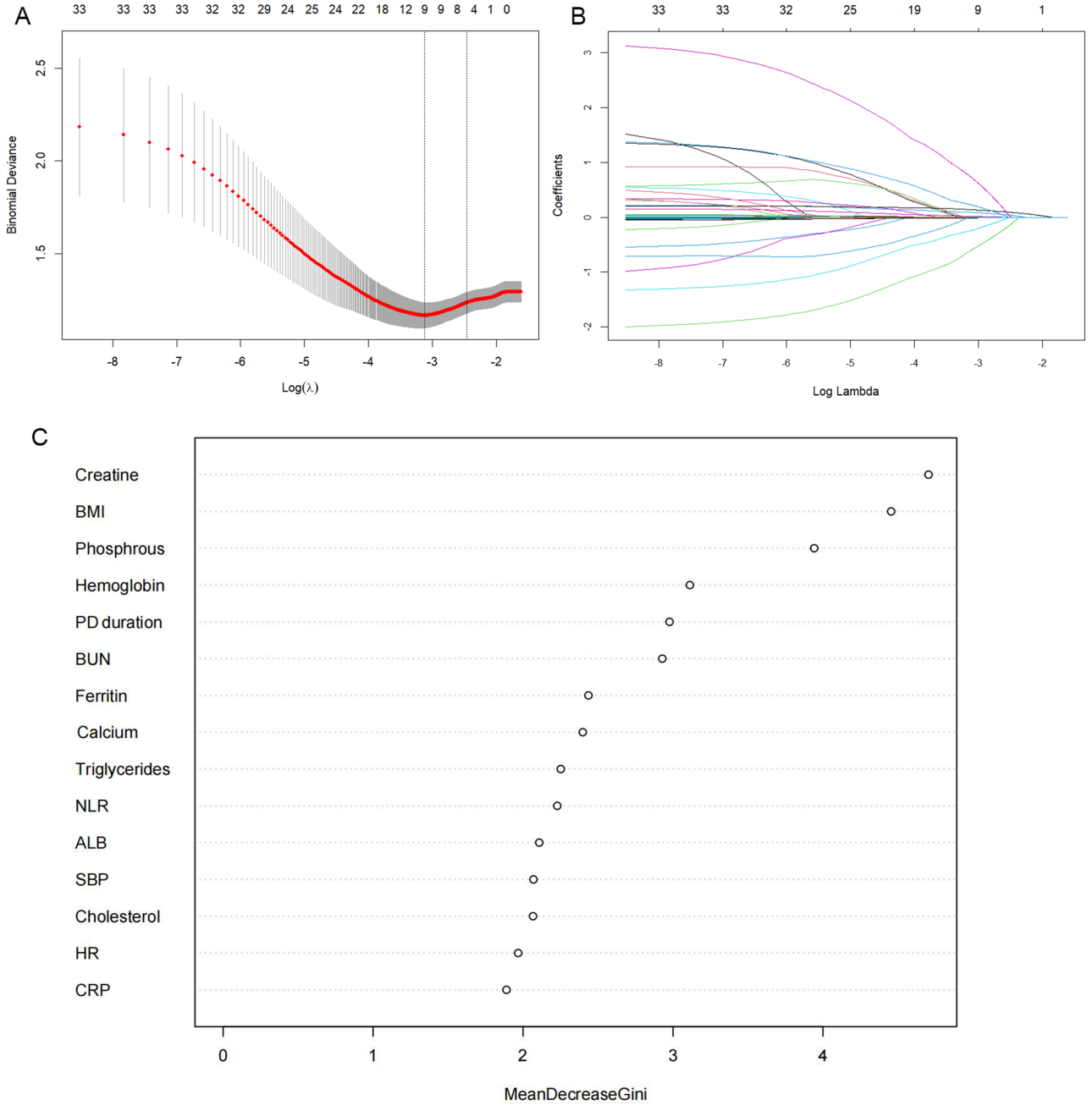

Fig. 2 Lasso regression and random forest algorithm to identify potential biomarkers

Kt/Vurea, as indicated by the points allocated in the nomogram.

Model evaluation

The internal validation process was implemented to assess the predictive model's ability to differentiate between cases of low Kt/V and to mitigate the risk of overfitting. The model demonstrated robust discrimination with a C-Index of 0.802 for the main study group and 0.787 for the validation subset. Calibration plots illustrated a strong correlation between the nomogram's predictive estimates and the empirical findings of no PD adequacy, as depicted in Fig. 4. Further analysis revealed that the Area Under the Curve (AUC) for the model's receiver operating characteristic (ROC) curve was 0.778, accompanied by a 95% confidence interval ranging from 0.686 to 0.870). This metric underscores the model's commendable predictive precision, as indicated in Fig. 5. We calculated the Area Under the Curve (AUC) for significant predictors from our multivariable analysis and observed that BMI and HB exhibited the highest AUC values, as depicted in Supplementary Fig. 1.

Table 2 Logistic regression analysis of predictors for low Kt/V_{urea} of PD patients

Variables	Univariate			Multivariate		
	OR	95%CI	*P* value	OR	95%CI	*P* value
Age (years)	1.011	0.983–1.039	0.46			
Gender,male	1.396	0.671–2.905	0.372			
BMI	1.236	1.099–1.39	0	1.30	1.13–1.51	<0.01*
SBP(mmHg)	1	0.985–1.016	0.963			
PBP (mmHg)	1.009	0.987–1.031	0.417			
Heart Rate	1.031	0.985–1.08	0.191			
Urine	0.402	0.18–0.897	0.02	0.40	0.13–1.11	0.09
Smoke	4.368	1.037–18.403	0.044	2.23	1.47–5.85	0.03*
Hypertension, n (%)	1.231	0.438–3.463	0.693			
Diabetes, n (%)	1.707	0.768–3.796	0.19			
Cardiovascular disease, n (%)	1.689	0.651–4.641	0.31			
Peritonitis history						
≥ 2	4.048	0.357–45.921	0.259			
1 time	1.818	0.786–4.206	0.162			
CRP (mg/L)	1.05	0.986–1.118	0.126			
NLR	1.103	1.009–1.205	0.03			
Hemoglobin (g/L)	0.978	0.959–0.997	0.021	0.97	0.94–0.99	<0.01*
Calcium (mmol/L)	1.189	0.362–3.908	0.776			
Phosphorus (mmol/L)	2.441	1.197–4.978	0.014	2.38	1.03–6.07	0.052
Creatinine (μmol/L)	1.002	1.001–1.003	0.005			
BUN (mmol/L)	1.057	0.99–1.128	0.095			
Albumin (g/L)	1.041	0.964–1.125	0.306			
Cholesterol (mmol/L)	1.113	0.826–1.5	0.483			
HDL(mmol/L)	0.656	0.206–2.085	0.475			
LDL(mmol/L)	1.169	0.742–1.842	0.501			
Triglycerides (mmol/L)	1.258	0.884–1.789	0.203			
iPTH (pg/ml)	1	0.999–1.002	0.666			
PD duration(year)	1.213	1.029–1.429	0.022	1.22	0.99–1.53	0.07
ALP (mmol/L)	0.997	0.991–1.004	0.404			
Ferritin(μg/L)	1.002	1–1.004	0.095			
Transferrin(g/L)	0.995	0.967–1.025	0.748			
PD membrane statue						
Low (%)	2.042	0.886–4.706				
Low average (%)	1.556	0.742–3.263	0.242			
High(%)	0.331	0.117–0.94	0.038*	0.20	0.046–0.722	0.02*
High average (%)	0.561	0191–1.648	0.293			

BMI: body mass index; NLR: Neutrophil-to-Lymphocyte Ratio, CRP: c-reactive protein, WBC: white blood cell, BUN: blood urea nitrogen, iPTH, intact parathyroid hormone, PD: peritoneal dialysis, ALP: Alkaline Phosphatase; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure; *: $p < 0.05$

Subsequently, we compared BMI, HB, and the nomogram model, finding that the nomogram demonstrated the largest AUC, indicating superior predictive performance.

Additionally, as shown in Fig. 6, the Decision Curve Analysis (DCA) confirmed the model's significant clinical utility, highlighting its effectiveness across a wide range of threshold probabilities from 1% to 94%. This finding further validates the model's ability to accurately predict the likelihood of peritoneal dialysis function decline in patients undergoing peritoneal dialysis.

Discussion

In this study, we developed and validated a nomogram to predict the risk of low Kt/V in PD patients, using a combination of demographic, clinical, and laboratory variables. Nomogram, one of the most effective clinical prediction models available, are commonly used in clinical practice to help clinicians assess patients at high risk of poor outcomes by providing an overall score. Our findings highlight the significant predictive power of key biomarkers and clinical factors, which have important implications for the early identification of patients at risk for inadequate PD.

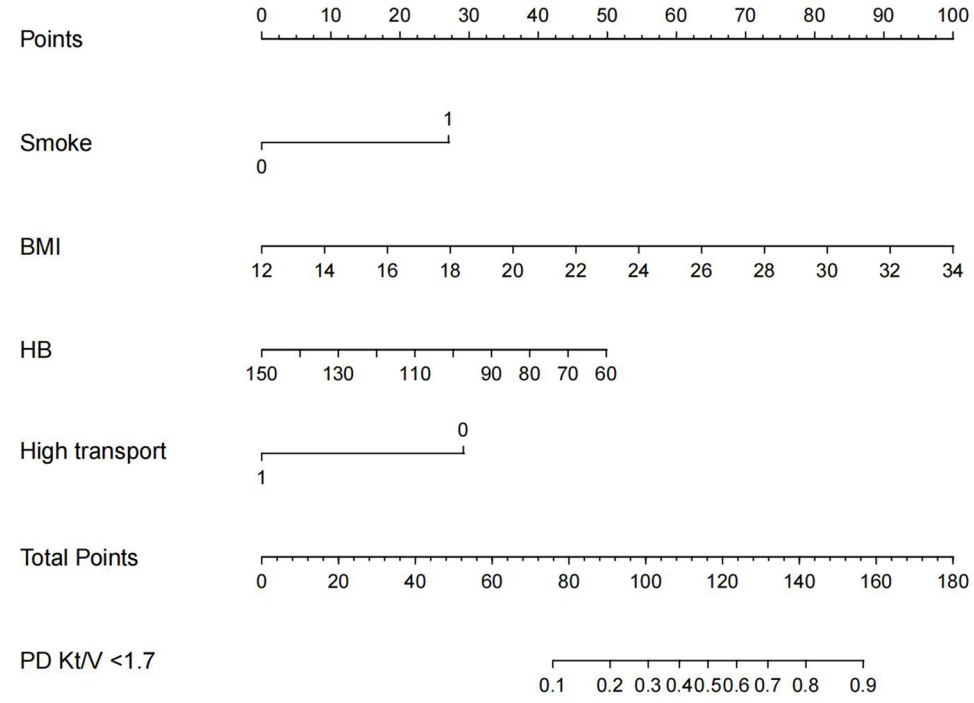

Fig. 3 Nomogram for predicting inadequacy of PD patients

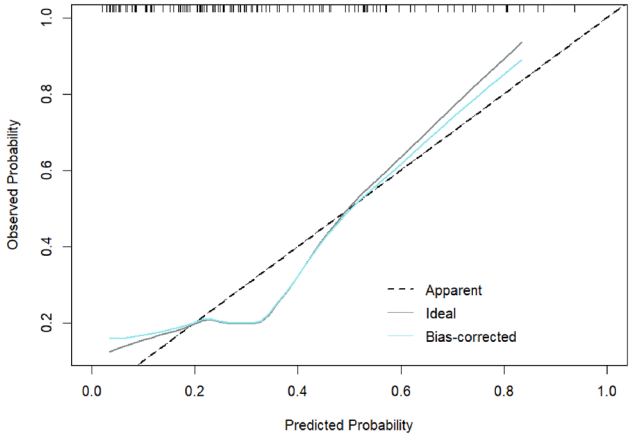

Fig. 4 Calibration plots of internal validation

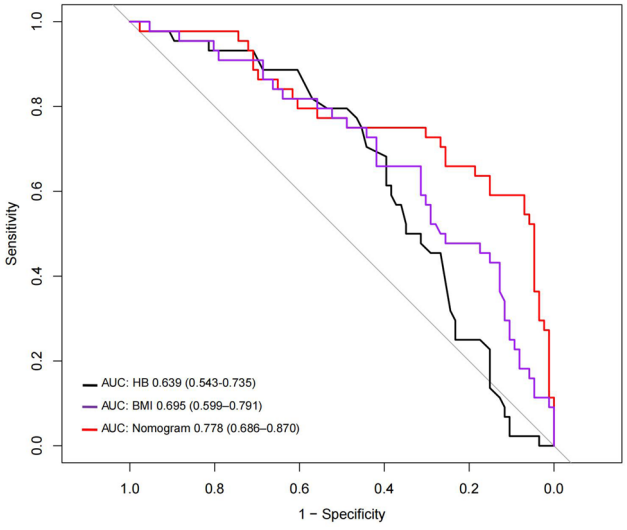

Fig. 5 Receiver operating characteristic curve of the nomogram, BMI and HB. AUC: area under curve, BMI: body mass index, HB: Hemoglobin

Dialysis adequacy is recognised as a key prognostic factor in CAPD patients. Assessment of PD adequacy plays an important role in improving quality of life and survival and reducing the technical failure rates. The Kt/V_{urea} is well recognized as a crucial indicator of dialysis adequacy and the elimination of tiny solutes [16]. The study cohort, comprising 141 incident PD patients, revealed significant differences between patients with adequate and inadequate PD as measured by Kt/V. The group with low Kt/V had a higher BMI and more high transporter, as well as lower levels of hemoglobin and albumin, which are consistent with previous researches linking these factors to suboptimal dialysis outcomes. Xu et,al found that higher BMI is associated with lower dialysis adequacy (low Kt/V). Increased body mass can lead to reduced peritoneal surface area relative to body size, impacting dialysis effectiveness [17]. Patients with high peritoneal transport have a strong solute clearance capacity, which allows them to quickly remove small-molecule toxins from the blood into the dialysate. Therefore, their Kt/V values are higher than those of low transporters [18]. Additionally, similarly with previous research, our study demonstrated PD patients with a Kt/V less than 1.7 have higher levels of phosphorus, BUN, and creatinine, which is may due

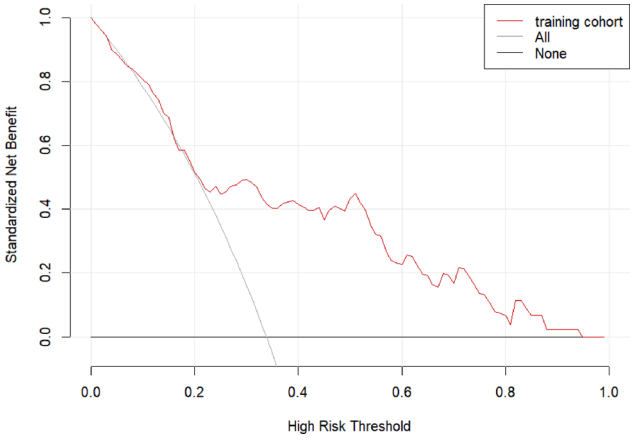

Fig. 6 Decision curve analysis curve of the nomogram

to the lower clearance efficiency of peritoneal dialysis for these solutes and possibly poorer residual kidney function.Even if they are consequences of inadequate dialysis, their early identification may still offer insights into patients at risk for further deterioration in PD Kt/V urea, facilitating timely intervention [19].

In the biomarker screening process, we employed univariate logistic regression, LASSO analysis, and Random Forest (RF) algorithms to identify potential predictors of low Kt/V. Univariate logistic regression highlighted significant associations for several variables, including BMI, urine output, smoking, NLR, hemoglobin, phosphorus, and PD duration, underscoring their potential relevance to PD adequacy. LASSO analysis, known for its effectiveness in handling multicollinearity [20], refined the model to include hemoglobin, PD duration, BMI, urine output, and creatinine as key predictors, selected through a 10-fold cross-validation process to minimize model error. RF algorithms, recognized for their robustness in variable selection despite noise and complex interactions [21], identified creatinine, BMI, phosphorus, BUN, and hemoglobin as the most important variables in predicting low Kt/V.These findings underscore the multifactorial nature of PD adequacy, with overlapping yet distinct predictors emerging from different methods. The identification of lifestyle factors such as smoking, alongside clinical parameters, highlights the importance of a comprehensive approach to patient assessment. This integrative strategy not only considers physiological variables but also addresses potentially modifiable risk factors, emphasizing the need for tailored interventions to optimize PD adequacy.

Our nomogram, constructed from these significant predictors, demonstrated strong predictive accuracy, with a C-Index of 0.802 in the main study group and 0.787 in the validation subset. The model's Area Under the Curve (AUC) of 0.778 further supports its robust discriminatory ability. Importantly, the nomogram outperformed individual biomarkers such as BMI and Hemoglobin, highlighting the added value of integrating multiple predictors into a single, user-friendly tool for clinical decision-making.This work is the first to develop a nomogram for predicting the likelihood of low kt/v in PD patients [11, 22]. It has the potential to offer clinical guidance for early identification and modification of prescriptions in PDAP patients who are at a high risk of experiencing low kt/V.

The Decision Curve Analysis (DCA) confirmed the nomogram's clinical utility across a wide range of threshold probabilities [23], indicating its potential to guide clinical interventions aimed at preventing PD inadequacy. This is particularly important given the complex and multifactorial nature of PD failure, where early identification of at-risk patients can lead to timely interventions, such as adjustments in dialysis prescription, nutritional support, or lifestyle modifications [24].

Despite the strengths of our study, including the use of multiple predictive modeling techniques and robust internal validation, there are some limitations to consider. First, the retrospective design and the single-center nature of the study may limit the generalizability of our findings. Additionally, a key limitation is the relatively small sample size, which may limit the external validity and generalizability of the findings.Future studies with larger, multicenter cohorts will be essential to validate the findings of this study and determine the model's true clinical utility in diverse patient populations. Moreover,our model does include PD duration as a variable, which may affect the assessment of patients who have just started dialysis.Our experiments in future should be designed more reasonably to be able to predict patient.

Although our study demonstrated that the nomogram is a potentially useful tool for predicting Kt/V in PD patients, its value could be further enhanced by providing additional practical guidance for clinicians on its application in real-world clinical settings. To this end, we envision developing the nomogram into a user-friendly digital tool, such as a mobile or desktop application. This tool would allow clinicians to input relevant patient information and receive real-time predictions based on the nomogram [25]. Additionally, the creation of a web-based interface is under consideration. Such a platform would include detailed instructions on data input and result interpretation, accompanied by illustrative examples and case scenarios to facilitate understanding and application [26]. By making the nomogram accessible across various devices, this approach would enhance its usability and integration into routine clinical practice, ultimately supporting more personalized and effective patient cares who are starting peritoneal dialysis.

Conclusion

In conclusion, this study presents a novel nomogram that effectively predicts the risk of low Kt/V in PD patients. By incorporating readily available clinical and laboratory variables, this tool offers a practical and accurate method for identifying patients at risk of PD inadequacy. Future research should focus on external validation of this nomogram and exploring its potential integration into routine clinical practice to improve patient outcomes in PD.

Abbreviations

ALP	Alkaline Phosphatase
AUC	Area Under the Curve
BMI	Body Mass Index
BUN	Blood Urea Nitrogen
CAPD	Continuous Ambulatory Peritoneal Dialysis
CRP	C-Reactive Protein
CVEs	Cardiovascular Events
DCA	Decision Curve Analysis
DBP	Diastolic Blood Pressure
HB	Hemoglobin
iPTH	Intact Parathyroid Hormone
Kt/Vurea	Urea Clearance Index
NKF KDOQI	Kidney Disease Outcomes Quality Initiative
NLR	Neutrophil-To-Lymphocyte Ratio
PD	Peritoneal Dialysis
PET	The Peritoneal Equilibration Test
RF	Random Forest
RKF	Residual Kidney Function
SBP	Systolic Blood Pressure
TBW	Total Body Water
WBC	White Blood Cell

Supplementary information

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Supplementary Material 1

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Author contributions

Danfeng Zhang participated in study design and manuscrpt draft. Tian Zhao are contribute to the performance of research and data collection. Liting Gao, Huan Zhu and Haowei Jin participated in the data collection. Guilin Liu is contributed to study design and perfomance of research. Deguang Wang is the senior author of this manuscript and contributed to the study design, implementation and manuscrpt draft. All authors reviewed the article and approved the submitted publication.

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Data availability

Due to ethical considerations and participant confidentiality, requests for access to the raw data should be directed to the corresponding author.

Declarations

Ethics approval and consent to participate

This study adhered to the Declaration of Helsinki and was approved by the Ethics Committee of The Second Hospital of Anhui Medical University (YX2022-014). Informed consent was obtained from all individual participants included in the study.

Consent for publication

Not applicable.

Clinical trial number

Not applicable.

Competing interests

The authors declare no competing interests.

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