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Incorporation of Chest Computed Tomography Quantification to Predict Outcomes for Patients on Hemodialysis with COVID-19

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Keywords
COVID-19 · Hemodialysis · Nomograms · Chest computed tomography · Risk factors

Abstract
Introduction: Patients undergoing maintenance hemodialysis are vulnerable to coronavirus disease 2019 (COVID-19), exhibiting a high risk of hospitalization and mortality. Thus, early identification and intervention are important to prevent disease progression in these patients. ***Methods:*** This was a two-center retrospective observational study of patients on hemodialysis diagnosed with COVID-19 at the Lingang and Xuhui campuses of Shanghai Sixth People's Hospital. Patients were randomized into the training (130) and validation cohorts (54), while 59 additional patients served as an independent external validation cohort. Artificial intelligence-based parameters of chest computed tomography (CT) were quantified, and a nomogram for patient outcomes at 14 and 28 days was created by screening quantitative CT measures, clinical data, and laboratory examination items, using univariate and multivariate Cox regression models. ***Results:*** The median dialysis duration was 48 (interquartile range, 24–96) months. Age, diabetes mellitus, serum phosphorus level, lymphocyte count, and chest CT score were identified as independent prognostic indicators and included in the nomogram. The concordance index values were 0.865, 0.914, and 0.885 in the training, internal validation, and external validation cohorts, respectively. Calibration plots showed good agreement between the expected and actual outcomes. ***Conclusion:*** This is the first study in which a reliable nomogram was developed to predict short-term outcomes and survival probabilities in patients with COVID-19 on hemodialysis. This model may be helpful to clinicians in treating COVID-19, managing serum phosphorus, and adjusting the dialysis strategies for these vulnerable patients to prevent disease progression in the context of COVID-19 and continuous emergence of novel viruses.

Introduction

As of December 13, 2023, the coronavirus disease 2019 (COVID-19) pandemic has infected over 770 million people and caused nearly seven million deaths [1]. Although the World Health Organization declared in May

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2023 that COVID-19 is no longer a global public health emergency, managing severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infections over the long run remains a problem. SARS-CoV-2 has been and will continue to circulate widely and evolve to evade vaccines, treatments, and population-wide immunity, and could potentially cause another devastating round of disease and death.

Individuals requiring in-center maintenance hemodialysis (MHD) due to end-stage renal disease are highly vulnerable and have been seriously threatened by the COVID-19 pandemic. Not only are they more likely than the general population to contract COVID-19, but they also exhibit higher disease severity and mortality [2–7]. Based on data from the OpenSAFELY project that analyzed 17 million patients with COVID-19, the ERA-EDTA Council and the ERACODA Working Group implied that dialysis is the most common cause of comorbidities and is most closely linked to COVID-19 death risk [8, 9]. Therefore, early assessment of progression and timely intervention are critical for these special populations. Several studies from Europe, America, and Turkey have reported indicators of COVID-19 severity in dialysis patients [10–13]. However, evidence from China is lacking, and it remains unknown what role radiographic indices play in the prognosis of patients with COVID-19 receiving hemodialysis.

Chest computed tomography (CT) is widely utilized as the primary imaging technique for screening, diagnosis, monitoring, and assessment of COVID-19. However, the subjectivity and experience of radiologists greatly limits the accuracy of the visual evaluation of CT images. The evolution of artificial intelligence (AI) technologies has helped solve this issue and made chest CT quantitative analysis a clinical reality. This automatic method has significant advantages of being fast and reproducible. Several studies have suggested that AI-driven CT quantification is useful in managing patients with COVID-19 by evaluating disease severity and forecasting clinical deterioration [14, 15]. Sun et al. [16] showed that patients with severe and non-severe COVID-19 had substantially varied quantitative pulmonary CT values, including ground-glass opacity (GGO) score, consolidation score, and total lesion score, and that the total lesion score exhibited the most excellent discriminative ability for assessing disease severity. Our previous work found that AI-based GGO volume was an independent risk factor for the prediction of acute renal damage and in-hospital death among patients with COVID-19 [17]. Although quantitative measures of chest CT were applied in patients with COVID-19 on hemodialysis by Tylicki et al. [18], the association between the quantitative features and short-term prognosis of patients with COVID-19 on MHD has never been studied. Furthermore, no reliable tools for assessing prognosis and clinical decision-making are available for this population. Thus, in this study, we aimed to determine the prognostic variables of COVID-19 in patients on MHD, establish and validate a prognostic nomogram incorporating quantitative chest CT parameters and clinical indicators, and provide better strategies for early intervention.

Methods

Study Design and Participants

This was a two-center retrospective study. Patients on hemodialysis that were diagnosed with COVID-19 between April 7 and May 25, 2022, in the Lingang Campus of Shanghai Sixth People's Hospital were divided into a 70% training cohort and a 30% internal validation cohort by random resampling. The facility was declared a designated hospital on April 3, 2022. By the end of May, it had received more than 200 patients with COVID-19 that had undergone MHD at different centers before infection. Patients diagnosed with COVID-19 in the Xuhui Campus between December 11, 2022, and January 20, 2023, served as an independent external validation cohort. The inclusion criteria were: (1) age >18 years, (2) end-stage renal disease treated by hemodialysis, (3) diagnosis of SARS-CoV-2 infection by a positive reverse transcriptase-polymerase chain reaction result in nasopharyngeal/throat swabs, and (4) CT scans performed within 3 days before or after the laboratory examinations. Patients with less than 1 month of hemodialysis vintage, admission less than 24 h, and incomplete clinical or laboratory data were excluded.

This study was reviewed and approved by the Ethics Committee for human research of the Shanghai Jiao Tong University Affiliated Sixth People's Hospital and was in accordance with the Declaration of Helsinki (Approval No. 2022-KY-055[k]). Written informed consent was obtained from all patients.

Data Collection

Patient information at hospital admission was collected from electronic medical records, including demographic and clinical data, comorbidities, and laboratory parameters. The demographic and clinical data included sex, age, dialysis information (dialysis vintage and access), and comorbidities (diabetes mellitus, hypertension, cardiovascular disease, and chronic respiratory disease). Laboratory findings included levels of leukocyte, lymphocyte, neutrophil, hemoglobin, platelet, D-dimer, albumin, serum uric acid, calcium, phosphorus, C-reactive protein (CRP), interleukin-6, and procalcitonin; neutrophil-to-lymphocyte ratio; and estimated glomerular filtration rate (eGFR).

Chest CT images were obtained at admission using a 128-slice multidetector CT scanner with patients in the supine position during a single inspiratory breath-hold. For quantitative analysis, we employed an Al-based software (PneumoniaDoc; ShuKun Network Technology, Beijing, China; https://en.shukun.net), which can automatically segment the lung/lobes and lung lesions. Segmented images were reviewed by a senior radiologist. Finally,

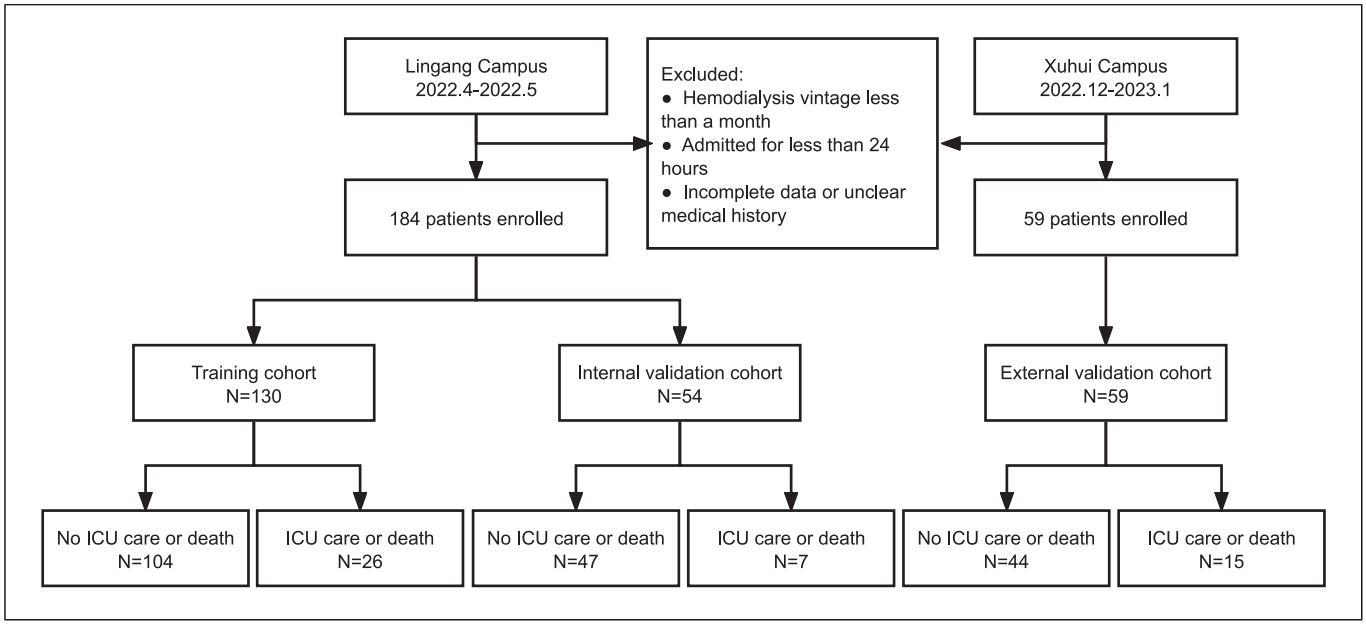

Fig. 1. Flowchart for the selection of the study population.

three quantitative features, the percentage of GGO volume (PGV), percentage of consolidation volume (PCV), and chest CT score (CCTS), were calculated. GGO was measured with an attenuation threshold of −750 to −300 Hounsfield units (HU) and consolidation with an attenuation threshold of −300 to 50 HU [17]. The CCTS is a semiquantitative chest CT scoring system that assesses the extent of parenchymal involvement. A 6-point scale (0 = 0%, 1 = 0–5%, 2 = 5–25%, 3 = 25–50%, 4 = 50–75%, 5 ≥75%) was assigned to each of the five lung lobes, and the five lobar scores were summed to calculate the final CCTS ranging from 0 to 25 [19]. The composite endpoint was admission to the intensive care unit (ICU) or death.

Statistical Analyses

For descriptive analysis, quantitative data were first analyzed for normality of distribution using the Shapiro-Wilk test. Normally, distributed data are presented as mean ± standard deviation (SD) and compared using the Student's *t* test. Non-normal data are presented as median with interquartile range (IQR) and compared using the Mann-Whitney U test. Categorical variables are presented as numbers with percentages and compared using the Pearson, χ^2, or Fisher's exact test. Univariate and multivariate Cox regression analyses were performed to determine the independent predictors of the composite outcome and to construct a nomogram using data in the training cohort. The performance of the nomogram was evaluated by discriminating and calibrating the internal and external cohorts. Discrimination was assessed using concordance index (C-index), and calibration was assessed using calibration plots. To further analyze the discrimination ability of the prognostic model, a risk score was calculated for each patient and used to classify the patients into low- and high-risk groups according to the median of the training cohort. Survival curves were plotted using the Kaplan-Meier method and compared using the log-rank (Mantel-Cox) test. Data analyses were performed using the IBM SPSS Statistics software (version 25.0) and R software (version 4.3.1). Statistical significance was defined as a two-tailed p value <0.05.

Results

Baseline Characteristics of Clinical and Laboratory Data

A total of 184 patients on hemodialysis with SARS-CoV-2 infection from the Lingang Campus, Shanghai Sixth People's Hospital, were included in the training (n = 130) and internal validation cohorts (n = 54). A total of 59 cases from the Xuhui Campus, Shanghai Sixth People's Hospital were recruited as an external validation cohort (shown in Fig. 1). The median follow-up durations for these cohorts were 62, 57, and 88 days, respectively. Table 1 displays the baseline clinical and laboratory characteristics of patients in each study group. The median age of the participants ranged from 65 to 68 years. The three cohorts had more males than females. The median time on dialysis of the 243 participants was 48 months (IQR, 24–96) months, and arteriovenous fistula was the predominant type of vascular access. Diabetes was one of the most common concomitant diseases in patients on dialysis with COVID-19, accounting for 27.7–39% of the three cohorts.

The median lymphocyte count ranged from 0.6×10^9/L to 0.7×10^9/L in the three cohorts. The median CRP

Table 1. Clinical and laboratory characteristics of the training, internal validation, and external validation cohorts

Variables	Training cohort (n = 130)	Internal validation cohort (n = 54)	External validation cohort (n = 59)
Clinical and demographic data			
ICU care or death	26 (20.0)	7 (13.0)	15 (25.4)
ICU care	12 (9.2)	3 (5.6)	8 (13.5)
Death	14 (10.8)	4 (7.4)	7 (11.9)
Males, n (%)	72 (55.4)	35 (64.8)	40 (67.8)
Age, years	65.00 (54.75, 73.00)	66.00 (59.00, 74.00)	68.00 (62.00, 74.00)
>65, n (%)	68 (52.3)	28 (51.9)	41 (69.5)
Comorbidity, n (%)			
DM	36 (27.7)	20 (37.0)	23 (39.0)
Hypertension	87 (66.9)	40 (74.1)	55 (93.2)
CVD	38 (29.2)	13 (24.1)	23 (39.0)
CRD	8 (6.2)	4 (7.1)	5 (8.5)
Dialysis vintage, months	48.00 (24.00, 96.00)	60.00 (27.00, 96.00)	44.07 (21.70, 80.03)
Dialysis access, n (%)			
Central venous catheter	23 (17.7)	11 (20.4)	12 (20.3)
AVF/AVG	107 (82.3)	43 (79.6)	47 (79.7)
Laboratory findings			
Leukocyte count, $\times 10^9$/L	4.74 (3.53, 6.17)	4.51 (3.62, 6.10)	4.90 (3.20, 6.80)
Lymphocyte count, $\times 10^9$/L	0.70 (0.50, 0.93)	0.70 (0.59, 1.08)	0.60 (0.50, 0.90)
Neutrophil count, $\times 10^9$/L	3.15 (2.25, 4.69)	3.05 (2.31, 4.23)	3.70 (2.30, 5.30)
Neutrophil-to-lymphocyte ratio	4.53 (2.81, 6.98)	3.82 (2.60, 6.37)	4.80 (3.30, 8.40)
Hemoglobin, g/L	102.00 (90.00, 111.25)	100.50 (91.00, 116.00)	109.00 (99.00, 117.00)
Platelet, $\times 10^{12}$/L	136.00 (102.00, 170.00)	144.00 (121.50, 181.00)	142.00 (103.00, 183.00)
D-dimer, mg/L	1.01 (0.57, 1.67)	1.16 (0.62, 1.94)	1.01 (0.52, 1.79)
Albumin, g/L	37.00 (35.00, 39.00)	37.00 (35.00, 41.00)	36.20 (30.95, 38.65)
Serum uric acid, μmol/L	517.62±118.21	525.09±134.14	422±100.39
eGFR, mL/min/1.73 m^2	3.75 (2.78, 5.16)	3.24 (2.51, 4.29)	3.94 (3.32, 4.89)
Calcium, mmol/L	2.22 (2.07, 2.37)	2.29 (2.09, 2.41)	2.06 (1.95, 2.20)
Phosphorus, mmol/L	2.30 (1.92, 2.83)	2.42 (1.80, 2.93)	1.75 (1.45, 2.26)
CRP, mg/L	9.06 (2.33, 30.21)	9.59 (3.90, 23.23)	24.35 (7.93, 78.67)
IL-6, pg/mL	17.61 (5.97, 47.72)	19.61 (7.24, 30.12)	30.81 (14.51, 141.15)
Procalcitonin, μg/L	0.41 (0.26, 0.67)	0.48 (0.34, 0.86)	0.85 (0.50, 1.61)

DM, diabetes mellitus; CVD, cardiovascular disease; CRD, chronic respiratory disease; AVF, arteriovenous fistula; AVG, arteriovenous graft; eGFR, estimated glomerular filtration rate; ICU, intensive care unit; CRP, C-reactive protein; IL-6, interleukin-6.

levels were 9.06 (IQR, 2.33–30.21) mg/L, 9.59 (IQR, 3.90–23.23) mg/L, and 24.35 (IQR, 7.93–78.67) mg/L, and the median serum phosphorus levels were 2.30 (IQR, 1.92–2.83) mmol/L, 2.42 (IQR, 1.80–2.93) mmol/L, and 1.75 (IQR, 1.45–2.26) mmol/L, in the training, internal validation, and external validation cohorts, respectively. Anemia was observed, with a median hemoglobin level of 100–109 g/L.

Chest CT Characteristics

For accurate evaluation of pathological lesions in the lungs, we employed AI-based software (shown in online suppl. Fig. S1; for all online suppl. material, see https://doi.org/10.1159/000539568), which can not only segment lung lobes and pneumonia lesions but also display the location and extent of lesions through 3D visualization. GGO and consolidation lesions can be automatically identified in axial images (shown in Fig. 2). Based on the software, we introduced three quantitative indicators, including CCTS, PGV, and PCV (shown in Table 2). CCTS is a semiquantitative scoring system used to assess the severity of lung inflammation, where PGV and PCV refer to the percentage of GGO and consolidation volume versus the total lung volume. Compared with those in the training cohort, patients in the external validation cohort showed milder pulmonary inflammation with a significant reduction in CCTS (4.00 [IQR, 2.00–7.00] vs. 5.00 [IQR, 5.00–6.00], p = 0.001),

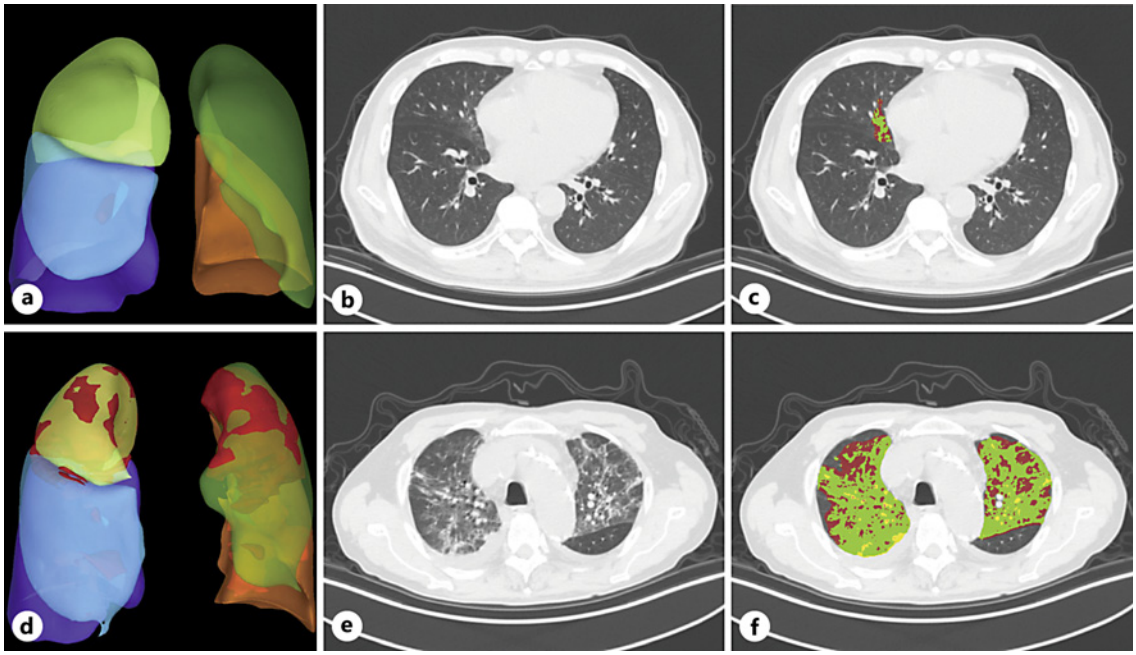

Fig. 2. Pneumonia lesions detected by the software PneumoniaDoc. Pictures showed a 60-year-old man with mild pulmonary inflammation (**a–c**), and a 68-year-old man with severe pulmonary inflammation who was transferred to the ICU after 7 days of admission (**d–f**). 3D visualization of five lobes in different colors, and pneumonia areas were indicated in red (**a**, **d**). Initial CT images were shown (**b**, **e**). AI-based quantitative features were shown in three pseudo colors which represented pneumonia in red, ground-glass opacity (GGO) in green, and consolidation in yellow (**c**, **f**).

Table 2. Chest CT quantitative characteristics of the training, internal validation, and external validation cohorts

Variables	Training cohort (n = 130)	Internal validation cohort (n = 54)	External validation cohort (n = 59)
AI-assisted quantification of chest CT			
CCTS	5.00 (5.00, 6.00)	5.00 (5.00, 7.00)	4.00 (2.00, 7.00)
PGV, %	0.61 (0.14, 3.13)	1.03 (0.12, 4.28)	0.16 (0.01, 0.04)
PCV, %	0.11 (0.02, 0.44)	0.11 (0.02, 0.72)	0.01 (0.00, 0.02)

CT, computed tomography; CCTS, chest CT score; PGV, percentage of GGO volume; PCV, percentage of consolidation volume; AI, artificial intelligence.

PGV (0.16 [IQR, 0.01–0.04] % vs. 0.61 [IQR, 0.14–3.13] %, $p < 0.001$), and PCV (0.01 [IQR, 0.00–0.02] % vs. 0.11 [IQR, 0.02–0.44] %, $p < 0.001$), suggesting enhanced immunity of patients due to prior infection, vaccination, or both.

Predictor Selection in the Training Cohort

To investigate prognostic factors, univariate and multivariate Cox proportional hazard analyses were performed. Univariate analysis showed that age, CVD, chronic respiratory disease (CRD), dialysis vintage, dialysis access, lymphocyte count, neutrophil count, neutrophil-to-lymphocyte ratio, albumin level, phosphorus, CRP, interleukin-6 level, procalcitonin level, CCTS, PGV, and PCV were significantly correlated with patient outcomes (shown in online suppl. Table S1). Factors with p values <0.1 were included in the subsequent Cox multivariate analysis. Results showed that age (hazard ratio [HR] = 1.081, 95% confidence interval [CI]: 1.033–1.130, $p < 0.001$), presence of diabetes mellitus

Table 3. Multivariate Cox regression analysis for the prediction of critical outcomes

Variables	Coefficients	HR	95% CI	*p* value
Age	0.078	1.081	(1.033–1.130)	<0.001
History of DM	1.120	3.063	(1.297–7.233)	0.011
Phosphorus (mmol/L)	0.572	1.773	(1.022–3.076)	0.042
Lymphocyte count ($\times 10^9$/L)	−3.080	0.046	(0.008–0.251)	<0.001
AI-assisted CCTS	0.213	1.237	(1.012–1.512)	0.038

HR, hazard ratio; CI, confidence interval; AI, artificial intelligence; CT, computed tomography; CCTS, chest CT score.

(HR = 3.063, 95% CI: 1.297–7.233, $p = 0.011$), lymphocyte count (HR = 0.046, 95% CI: 0.008–0.251, $p < 0.001$), phosphorus level (HR = 1.773, 95% CI: 1.022–3.076, $p = 0.042$), and CCTS (HR = 1.237, 95% CI: 1.012–1.512, $p = 0.038$) were independent prognostic factors in patients on hemodialysis with COVID-19 (shown in Table 3). These data suggest that patients with advanced age, diabetes, lower lymphocyte counts, higher phosphorus levels, and higher CCTS had worse outcomes.

Prognostic Nomogram Development

Based on these five variables, we constructed a prognostic nomogram integrating demographic, clinical, and laboratory features along with chest CT quantitative data to predict the 14- and 28-day survival probabilities of patients on hemodialysis infected with SARS-CoV-2 (shown in Fig. 3). For example, a 74-year-old patient with diabetes and a phosphorus level of 1.81 mmol/L, lymphocyte count of 0.71 × 10^9/L, and CCTS of 5 would obtain a total score of 127, corresponding to estimated 14- and 28-day survival likelihoods of 79% and 76%, respectively.

Model Verification

Validation results for the model showed good discrimination and calibration. The C-indexes were 0.865 (95% CI: 0.810–0.919), 0.914 (95% CI: 0.819–1.008), 0.885 (95% CI: 0.773–0.997) for the training, internal validation, and external validation cohorts, respectively, indicating favorable discrimination ability of the nomogram. As shown in Figure 4, the diagonal dotted line represents a perfect agreement between prediction and observation and two solid curves represent the calibration curve. Calibration curves were close to the diagonal in three cohorts, indicating good calibration ability of the nomogram. To further validate the universality of the prognostic model, each patient's risk score was calculated, and the patients were then categorized into high- and low-risk groups based on the median score of the training cohort. The Kaplan-Meier curve illustrated that the model performed well in distinguishing between high- and low-risk individuals (shown in Fig. 5).

Discussion

Considering the uncertainties and recurrent infections with SARS-CoV-2, COVID-19 remains a major health concern that requires global attention in the post-COVID-19 pandemic era. A retrospective observational research revealed a 4.89-fold increased risk of reinfection in the Omicron phase compared with the Delta phase and that patients undergoing dialysis had an approximately threefold higher risk of reinfection than patients not undergoing dialysis among those with chronic renal failure [20]. Investigating the characteristics and prognosis of patients on hemodialysis with COVID-19 is crucial to reducing the risk of adverse outcomes and optimize management strategies for the new normal of daily life after COVID-19.

Multiple predictors are reportedly involved in poor outcomes for COVID-19 among patients on dialysis [10–12, 21, 22]. Abnormal laboratory indicators, including increased CRP, D-dimer, bilirubin, type B natriuretic peptide, and decreased lymphocytes levels, were associated with worse short-term survival in studies from France, the USA, and China [10, 12, 22]. Clinical symptoms such as fever and malnutrition at the time of swabbing were related to 30-day mortality in an Italian study [11]. Comorbidities such as heart disease, peripheral vascular disease, and diabetes were also risk factors for disease severity [12, 21, 23]. However, the role of quantitative imaging parameters in the prognosis of patients on hemodialysis with COVID-19 has not been evaluated. Currently, no reliable tools exist for prognostic assessment or clinical decision-making in this population. Therefore, we constructed a novel nomogram incorporating quantitative

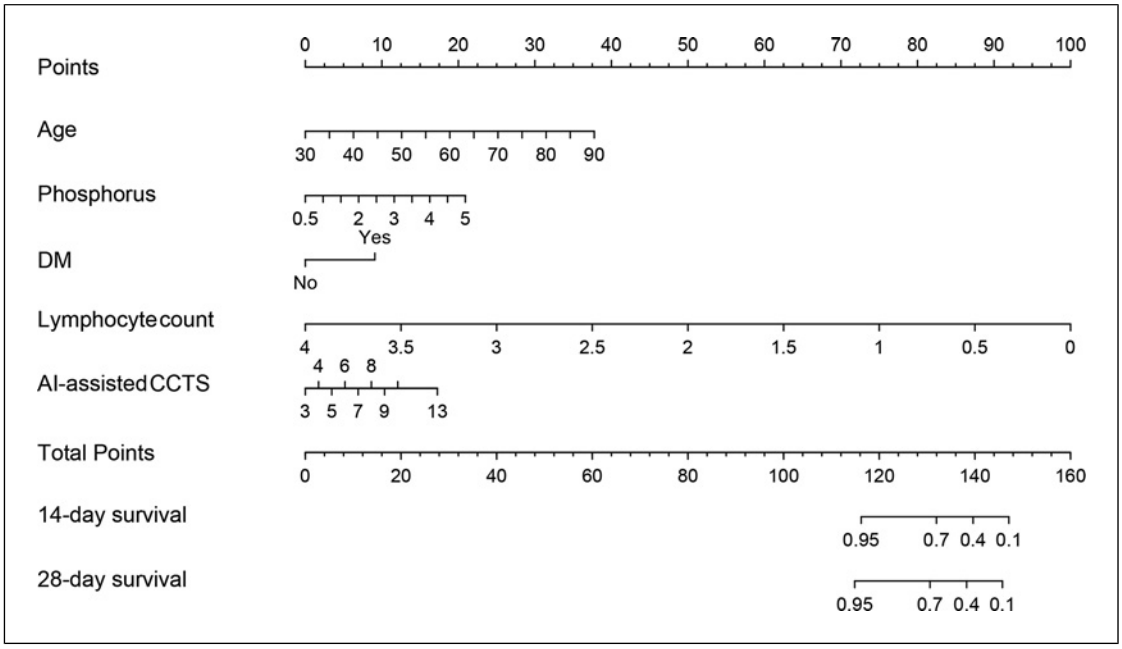

Fig. 3. Nomogram for the prediction of ICU admission or death after 14 and 28 days in patients on hemodialysis with COVID-19.

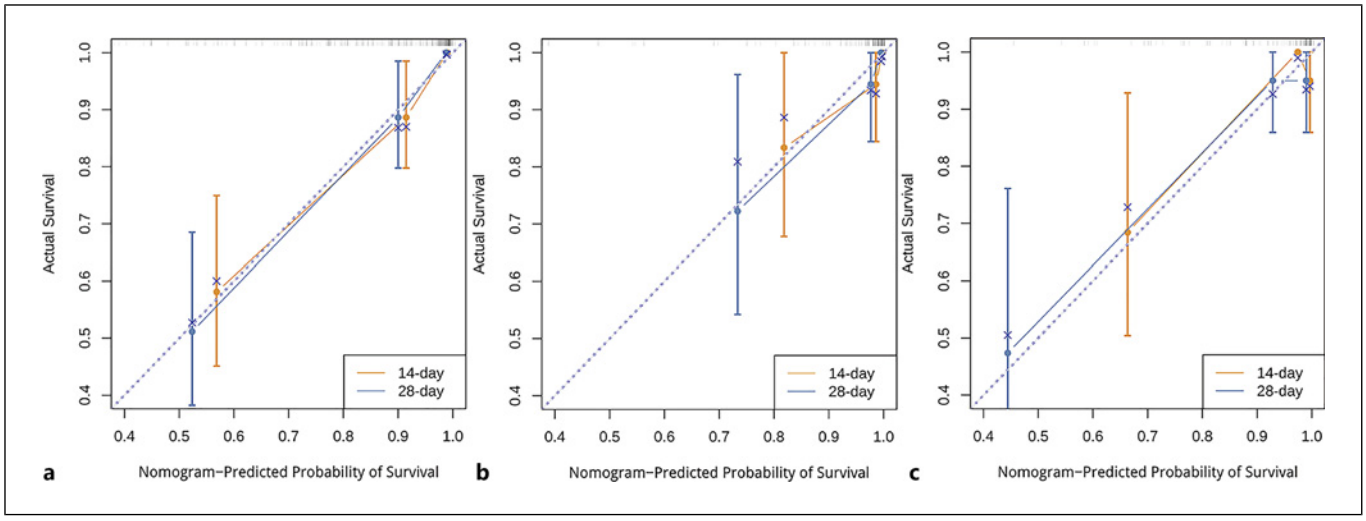

Fig. 4. Calibration curves of the nomogram in the training cohort (**a**), internal validation cohort (**b**), and external validation cohort (**c**).

chest CT parameters and clinical indicators to predict the 14- and 28-day survival rates of patients on hemodialysis with COVID-19 and validated its performance internally and externally.

AI-based quantification has been widely used in chest CT imaging, which could reliably, accurately, and efficiently evaluate the distribution range and severity of pneumonia on CT scans through automatic segmentation of normal lung architectures and pulmonary pathologies [24–26]. This study described three COVID-19 chest CT features (PGV, PSV, and CCTS) calculated by computer software in patients on dialysis and was the first to report CCTS as a significant predictor of prognosis for these patients. The CCTS is a semiquantitative scoring system with a total score of 25. Compared with other semiquantitative scoring systems evaluating the severity of

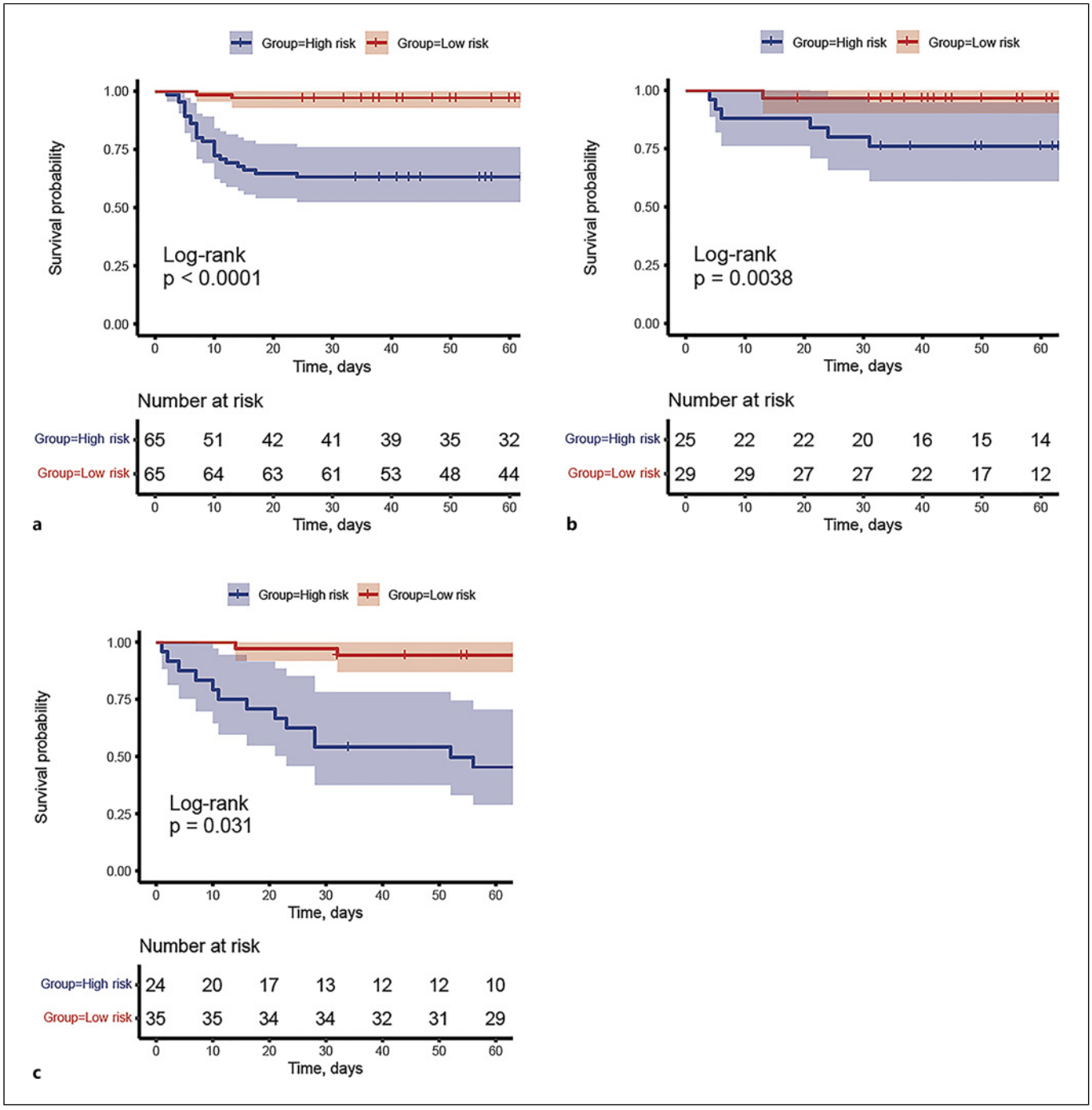

Fig. 5. Kaplan-Meier curves for overall survival in the high-risk and low-risk groups (based on the total score of the predictive nomogram at the threshold of 120.36 points) in the training cohort (**a**), internal validation cohort (**b**), and external validation cohort (**c**).

pulmonary lesions, it had the highest specificity in distinguishing critical cases and is considered the most suitable approach for clinical use [27, 28]. Li et al. [29] found that increased chest CT score and number of affected pulmonary lobes on CT scans performed within the first few days were substantially related to COVID-19 mortality. Feng et al. [30] showed that CT severity score was associated with inflammation and was an independent

risk factor for short-term progression. The results from the present study were consistent with the above findings, further highlighting the significance of CCTS in predicting the prognosis of patients on MHD with COVID-19.

As a hallmark of chronic kidney disease-mineral and bone disorder, hyperphosphatemia is particularly prevalent in patients with end-stage renal disease receiving maintenance dialysis. High concentrations of serum phosphorus are related to an increased risk of cardiovascular incidents and mortality through multiple pathophysiological mechanisms including calcification of vascular smooth muscle cells, endothelial dysfunction, elevated fibroblast growth factor-23 concentrations, and high parathyroid hormone concentrations [31]. In agreement with the findings of this study, Akchurin et al. [32] found that pre-COVID-19 and admission serum phosphorus levels were associated with in-hospital mortality in patients with chronic kidney disease. Data from a dialysis center in Portugal suggested that COVID-19 lockdown may lead to decreased dialysis adequacy and increased serum phosphorus levels of patients [33]. Reduced dialysis frequency and duration of dialysis per session may explain decreased dialysis adequacy, which further contributes to the elevated phosphorus levels. In addition, increased consumption of phosphorus-containing foods and failure to regularly take phosphate binders can lead to poor serum phosphorus control. Even without the lockdown policy, an increase in serum phosphorus levels was observed during the pandemic [34]. Therefore, phosphate management is an essential strategy for managing patients on in-center MHD in the context of COVID-19. To achieve this optimal target, limited dietary phosphorus intake, phosphate binder therapy, and adequate dialysis are required.

In this study, multivariate analysis revealed that age, lymphocyte count, and diabetes were independent prognostic factors in patients on hemodialysis with COVID-19. Older patients and those with lymphocytopenia tend to have worse prognosis owing to impaired immune function; thus, they should receive additional medical attention. Moreover, patients with diabetes on hemodialysis should strictly control their blood glucose levels and be prioritized for COVID-19 prevention measures, such as SARS-CoV-2 vaccination, to improve the prognosis of this population [35].

This is the first study in which a nomogram was constructed to predict adverse events of patients on MHD after SARS-CoV-2 infection. The model exhibited excellent discrimination and calibration abilities in both internal and external cohorts, confirming its robustness and extrapolation. We focused on short-term prognosis because death rates from 28 days to 3 months after COVID-19 diagnosis were low, and most of the survivors reached their pre-diagnostic state 3 months later [36]. Nevertheless, this study has some limitations. First, this was a retrospective, observational analysis with a limited number of patients on hemodialysis recruited solely from Shanghai, which inevitably introduced a selection bias. Therefore, further validation among individuals of other ethnicities and geographical areas is essential. Second, the study focused on in-center patients on hemodialysis and did not include patients undergoing home or peritoneal dialysis. Finally, comprehensive laboratory data and dialysis adequacy indicators, such as Kt/V and urea reduction ratio, were deficient owing to quarantine and limited medical resources during the COVID-19 pandemic. Adding these variables in future studies may improve the accuracy of the nomogram in this study.

In conclusion, a reliable nomogram was developed using clinical indicators and AI-based CT imaging parameters to predict outcomes and survival probabilities in patients with COVID-19 on hemodialysis. COVID-19 is not the first pandemic the world has faced, and neither will it be the last. New pandemics and emerging viruses continue to threaten human health. It should be borne in mind that patients on MHD are always more susceptible and vulnerable in pandemics, epidemics, and to infectious diseases. The results of this study indicate that multiple aspects, including comorbidities, dialysis adequacy, phosphorus homeostasis, inflammatory indicators, and chest CT quantification findings should be considered in the comprehensive assessment and management for early intervention to improve outcomes of this special population.

Statement of Ethics

This study was reviewed and approved by the Ethics Committee for human research of the Shanghai Jiao Tong University Affiliated Sixth People's Hospital and was in accordance with the Declaration of Helsinki, Approval No. (2022-KY-055[k]). Written informed consent was obtained from all patients.

Conflict of Interest Statement

The authors declare no conflict of interest.

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Author Contributions

Ying Fan and Hengye Huang conceived and designed the research project. Li He, Qiye Liu, and Haoran Feng collected the clinical data. Xiaoer Wei provided quantitative CT data. Hengye Huang, Haifan Xing, and Ze Li analyzed the data. Haifan Xing and Sijie Gu drafted the manuscript. Ying Fan and Niansong Wang revised the manuscript. All authors contributed to the article and approved the submitted version.

Data Availability Statement

The data supporting this study's findings are not publicly available due to privacy reasons but are available from the corresponding author Y.F. upon reasonable request.

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