Original Article

Construction and Verification of Clinical Prediction Models of Peritoneal Dialysis-Associated Peritonitis

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Abstract

Objective: To develop clinical predictive models (CPMs) for estimating the risk of peritoneal dialysis-associated peritonitis (PDAP) and to inform clinical management. **Methods:** Retrospective data on clinical, psychological, sleep, and mental aspects of 392 Parkinson's disease patients were gathered. Single factor analysis, LASSO Cox regression analysis, and logistic regression analysis were employed to develop the CPMs of PDAP. The CPMs were validated using the Area Under Curve (AUC), Calibration Curve, and Hosmer-Lemeshow (H-L) Test, with visualisation through Nomogram and Decision Curve Analysis (DCA) to assess the clinical efficacy of the CPMs for PDAP. **Results:** Of the 392 monitored Parkinson's disease patients, 69 exhibited Parkinson's disease-associated psychosis, or 17.60%. There were 120 instances of PDAP, with 33 patients experiencing recurrent occurrences, resulting in an incidence of 0.31 episodes per patient per year. The risk factors influencing the incidence of PDAP included serum potassium ([OR] 0.407, 95%[CI] 0.235-0.704; P=0.001), serum albumin ([OR] 0.890, 95%[CI] 0.827-0.958; P=0.002), triglycerides ([OR] 1.653, 95%[CI] 1.246-2.192; P<0.001), MMSE ([OR] 0.740, 95%[CI] 0.635- 0.862; P<0.001), PD patients with catheter and tunnel exit infection ([OR] 47.552, 95%[CI] 7.130- 317.112; P<0.001), and PD patients with diabetes mellitus ([OR] 2.961, 95%[CI] 1.116-7.861; P=0.029). The CPMs of PDAP were developed and illustrated using six variables. The AUC of the CPMs was 0.856 (95% CI 0.782-0.927) and 0.863 (95% CI 0.752-0.973), respectively. The Calibration Curves for both the modelling and verification groups approximate a straight line with a slope of 1, signifying the model's strong predictive capability. The DCA of both the modelling and verification groups exhibited a threshold ranging from 5% to 98%, with the DCA curve positioned in the top right quadrant relative to the reference line, indicating that the decision curve possesses substantial clinical applicability. **Conclusions:** This work created and validated a novel CPM for forecasting the incidence of PDAP.

Keywords: Peritoneal Dialysis, Peritonitis, Incidence, Risk Factors, Clinical Prediction Models.

Introduction

The literature indicates that there are 850 million individuals globally affected by chronic kidney disease (CKD).[1] Peritoneal dialysis (PD) is a primary therapy modality for chronic kidney disease (CKD) advancing to end-stage renal disease (ESRD). Worldwide, around 272,000 individuals undergo peritoneal dialysis,

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representing 11%[2] of the worldwide dialysis population, with 140,500[3] of these patients located in China. Peritoneal dialysis-associated peritonitis (PDAP) is a significant complication in patients undergoing peritoneal dialysis, resulting in alterations to peritoneal structure, increased hospitalisation, financial strain, and elevated mortality risk. It is regarded as the most critical indicator in the standardised prognosis plan for peritoneal dialysis nephropathy by patients, nursing staff, and clinicians. Numerous and intricate risk variables contribute to PDAP,[4-7] including uncontrollable elements such as age, gender, race, and coexisting cardiac diseases.[4,5] Certain aspects are controlled, including social, environmental, medical, and dialysis-related factors.[6] Moreover, research indicates that psychosocial and cognitive impairments are independent risk factors for people with PDAP.[7]

Clinical prediction models (CPMs), often referred to as clinical prediction rules, risk prediction models, predictive models, or risk scores, utilise mathematical formulas to assess the likelihood of an individual experiencing a given disease or event in the future.[8-10] CPMs encompass diagnostic and prognostic models. The essence of predictive diagnosis involves assessing the likelihood that a particular outcome or condition is present (or absent) in an individual at the exact moment of prediction. Prognosis entails predicting whether an individual encountered a particular occurrence or outcome within a defined timeframe. In diagnostic prediction, the focus is mostly on a cross-sectional relationship, while prognostic prediction pertains to a longitudinal relationship. In diagnostic modelling investigations, a time interval between the measurement of predictors (index test) and the reference standard is frequently required for logistical reasons. This time should be minimised and no therapy should commence during this period.[9]

Forecasting the prevalence of PDAP is an essential component of contemporary health management. Developing and implementing a risk prediction model for PDAP, identifying high-risk populations, and executing hierarchical management can advance the preventive measures against PDAP. Simultaneously, it can alleviate the agony and financial burden of Parkinson's disease patients, and potentially enhance their prognosis. CPMs integrate various factors to predict the likelihood of adverse events for a specific patient. This study involves developing a risk prediction model for PDAP through prospective cohort studies, assessing the model's discrimination, calibration, and clinical applicability, and ultimately presenting the model as a Nomogram to serve as a visual predictive tool for the likelihood of associated peritonitis in peritoneal dialysis.

Methods

Study Population

A retrospective analysis gathered data from January 1, 2016, to November 31, 2024, across three Grade III hospitals located in southern (Nantong), central (Yancheng), and northern (Xuzhou) Jiangsu Province, China. Inclusion criteria: (1) Patients with Parkinson's disease (PD) who have had regular follow-up for at least three months; (2) Age 18 years or older; (3) Possession of adequate reading and communication skills; (4) Completion of baseline data; (5) Willingness to participate in the study. Exclusion criteria: (1) Age under 18 years; (2) History of malignancy; (3) Illiteracy; (4) Communication difficulties; (5) Blindness or deafness; (6) Prior renal replacement therapy before peritoneal dialysis; (7) Lack of willingness to participate in the study.

This study comprised 392 patients with Parkinson's disease (PD), comprising 160 patients from Nantong Hospital, 98 from Yancheng, and 134 from Xuzhou. The study was approved by the Ethics Committee of the hospital (LS-2024-100). All participants provided informed consent and executed a written consent form.

Data Collection

Patient information is acquired through two methods: electronic medical records and trained researchers conducting questionnaire consultations during patient follow-up or hospitalisation. This includes basic information, comorbidities, social and environmental factors, medical factors, dialysis-related factors, and infection-related factors.Fundamental information include gender, age, nationality, marital status, employment position, annual income, medical insurance coverage, and educational history. Comorbidities refer to Parkinson's Disease patients with Diabetes Mellitus (DM), Cardiovascular Disease (CVD), Lung-Related Disease (LRD), Cerebrovascular Disease (CBVD), Residual Renal Failure (RRF), anaemia, Systemic Lupus Erythematosus (SLE), pituitary tumours, gout, and secondary hyperparathyroidism (SHPT). Social and environmental factors encompass the weight and body mass index (BMI) of Parkinson's disease (PD) patients, smoking habits, pet ownership, proximity to the PD centre, climatic conditions, mental health (assessed via the Self-Rating Anxiety Scale (SAS), Self-Rating Depression Scale (SDS), and Mental Resilience Scale), sleep quality (evaluated using the Pittsburgh Sleep Quality Index (PSQI)), and cognitive function (measured by the Mini-Mental State Examination (MMSE)). Medical parameters encompassing serum calcium, serum potassium, serum phosphorus, haemoglobin (Hb), serum albumin, C-reactive protein (CRP), intact parathyroid hormone (iPTH), alanine aminotransferase (ALT), cholinesterase, triglycerides, creatinine, creatine kinase, alkaline phosphatase, serum uric acid (SUA), and blood urea nitrogen (BUN). Factors associated with dialysis encompass the dialysis method, duration of dialysis, quantity of 24-hour fluid exchange bags, catheter insertion technique, home operator, and the concurrent use of haemodialysis (HD). Infection-associated variables encompassing pulmonary infection, gastrointestinal infection, and infections at catheter and tunnel exit sites.

Patient demographics were extracted via the online systems of each hospital, while psychological and sleep assessments for PD patients were administered through standardised

paper questionnaires by uniformly trained investigators on-site, utilising consistent instructional language to assist patients in completing the questionnaires. This study distributed 400 questionnaires, all of which were returned, resulting in a recovery rate of 100%. However, 8 questionnaires were discarded due to incomplete responses, yielding 392 valid questionnaires and an effective rate of 98%. The patient's psychological condition was evaluated by consistently qualified professional personnel.

Outcome Measurements

The outcome of this study indicated the incidence of PDAP, with peritonitis diagnosed clinically during the follow-up period based on the presence of any two of the following characteristics: (1) Clinical manifestations consistent with peritonitis, including abdominal pain and/or murky dialysate; (2) white blood cell count in dialysate over 100/μL after a dwell duration of no less than 2 hours, with polymorphonuclear leukocytes constituting over 50%; and (3) positive culture results from the dialysate.

Statistical Analysis

A random number generator was employed to partition the acquired data into a modelling group (comprising 70%) and a verification group (comprising 30%). In the baseline analysis, means ± standard deviations are reported for normally distributed variables, medians and 25th–75th percentiles for nonparametric variables, and frequencies and percentages for categorical parameters. Comparisons between the two groups were analysed using t-tests, Mann–Whitney U tests, or chi-square tests, as applicable. Univariate analysis, LASSO regression analysis, and logistic regression analysis were employed to determine the CPMs of PDAP ($P<0.05$). We employed receiver operating characteristic (ROC) analysis and the area under the curve (AUC) to assess the predictive accuracy of the CPMs of PDAP. A nomogram was developed utilising the CPMs. Calibration plots were generated using bootstraps with 1000 resamples. All statistical analyses were conducted using R software version 4.1.2, with a significance threshold of $P < 0.05$.

Results

Baseline Characteristics

The demographic data of 392 Parkinson's disease patients revealed an average age of 49.74 years (±12.52), with the youngest patient being 21 years old and the oldest 85 years old. Among the cohort, 234 patients were male (59.69%) and 158 were female (40.31%). The majority, 390 patients, identified as Han (99.49%). Marital status included 22 unmarried patients (5.61%), 350 married patients (89.29%), 16 divorced patients (4.08%), and 4 widowed patients (1.02%). There were 244 unemployed patients (62.24%), 74 employed patients (18.88%), 45 retired patients (11.48%), and 29 individuals in other categories (7.40%). Out of the total, 330 patients (84.18%) had an annual income of < RMB 50,000, 52 patients (13.27%) had an annual income between RMB 50,000 and RMB 150,000, 6 patients (1.53%) had an annual income between RMB 150,000 and RMB 300,000, and 4 patients (1.02%) had an annual income of ≥ RMB 300,000. 160 patients (40.82%) were insured by rural medical insurance, 224 patients (57.14%) were insured under general employee medical insurance, and 8 patients (2.04%) were insured under alternative medical insurance. Thirty patients (7.65%) possessed basic school education, 176 patients (44.90%) had junior high school education, 140 patients (35.71%) were educated at the senior high school or technical secondary school level, and 46 patients (11.73%) held junior college or undergraduate degrees. The comorbidities of 392 Parkinson's disease patients included: Out of 392 Parkinson's disease patients, 55 (14.03%) experienced problems from diabetes mellitus, 242 (61.73%) had cardiovascular disease, 16 (4.08%) suffered from cerebrovascular disease, 66 (16.84%) were diagnosed with anaemia, 6 (1.53%) had systemic lupus erythematosus, 4 (1.02%) presented with pituitary tumours, and 18 (4.59%) had gout; additionally, 12 (3.06%) patients were affected by secondary hyperparathyroidism. The social and environmental characteristics of 392 patients with Parkinson's Disease (PD) are as follows: the mean body weight was 63.07±11.23 kg, with the lightest patient weighing 40.00 kg and the heaviest 90.00 kg; the average Body Mass Index (BMI) was 22.76±3.64, with a minimum BMI of 10.10 and a maximum of 34.96; there were 380 non-smokers (96.94%) and 12 smokers (3.06%); 326 patients (83.16%) did not own pets, while 66 patients (16.84%) did, predominantly cats or dogs; 176 patients (44.90%) travelled ≤1 hour by car to the PD centre, 136 patients (34.69%) travelled 1-2 hours, 44 patients (11.22%) travelled 2-3 hours, and 36 patients (9.18%) travelled ≥3 hours; 134 patients (34.18%) resided in Xuzhou City, 160 patients (40.82%) in Nantong City, and 98 patients (25.00%) in Yancheng City. The overall mean scores were as follows: SDS (54.05 ± 11.85), SAS (45.77 ± 8.91), CD-RISC (69.31 ± 24.53), PSQI (7.72 ± 3.99), and MMSE (26.95 ± 2.63). The medical characteristics of 392 people with Parkinson's disease included: The mean serum calcium was (2.16 ± 0.25) mmol/L; serum phosphorus was (1.90 ± 0.62) mmol/L; serum potassium was (4.25 ± 0.80) mmol/L; serum albumin was (37.25 ± 5.63) g/L; iPTH was (668.42 ± 539.16) pg/ml; ALT was (20.62 ± 11.88) U/L; cholinesterase was (6665.72 ± 1267.64) U/L; triglyceride was (2.03 ± 1.23) mmol/L; creatinine was (675.69 ± 589.52) umol/L; SUA was (427.19 ± 120.19) umol/L; BUN was (22.62 ± 6.87) mg/dL; the median of Hb was 106.00 g/L; the median of CRP was 1.28 mg/L; the median of alkaline phosphatase was 88.80 U/L. The dialysis-related characteristics of 392 patients undergoing peritoneal dialysis (PD) included: a dialysis duration ranging from a minimum of 1 month to a maximum of 96 months, with an average duration of (16.35±20.09) months; the number of dialysate bags varied from 2 to 6, with an average of (4.02±0.77) bags;

248 patients (63.27%) utilised continuous ambulatory peritoneal dialysis (CAPD), 118 patients (30.10%) employed automatic peritoneal dialysis (APD), and 26 patients (6.63%) underwent intermittent peritoneal dialysis (IPD); regarding dialysate bags per day, 21 patients (5.36%) used 2 bags, 47 patients (11.99%) used 3 bags, 233 patients (59.44%) used 4 bags, 87 patients (22.19%) used 5 bags, and 4 patients (1.02%) used 6 bags; 368 patients (93.88%) performed self-operation, while 24 patients (6.12%) were assisted by family members or carers. Out of 392 patients, 322 (82.14%) underwent treatment with peritoneal dialysis (PD) exclusively, while 70 (17.86%) were administered haemodialysis (HD) concurrently with PD. Among them, 232 patients (59.18%) utilised a Tenckhoff straight tube, 88 patients (22.45%) employed a Swan-neck straight tube, and 72 patients (18.37%) utilised a Swan-neck coil tube. Among 392 PD patients, the infection-related variables were as follows: 6 patients (1.53%) experienced lung infections; 7 patients (1.96%) had intestinal infections; and 17 patients (4.34%) suffered from catheter and tunnel exit infections.

Incidence of PDAP

Of the 392 monitored Parkinson's disease patients, 69 exhibited Parkinson's disease-associated psychosis, or 17.60%. There were 120 instances of PDAP, with 33 patients experiencing recurrent occurrences, resulting in an incidence rate of 0.31 episodes per patient-year.

Univariate Analysis of PDAP

Univariate analysis was performed based on the occurrence of PDAP during the follow-up of PD patients. Table 1 presents the baseline features of PDAP incidence. In comparison to other PD patients, those who experienced PDAP exhibited a higher frequency of dialysate bags per 24 hours, reduced serum potassium, diminished serum albumin, lower ALT levels, elevated triglycerides, a decreased total score on the MMSE, varied educational backgrounds, and a higher incidence of catheter and tunnel exit infections as well as diabetes mellitus (P<0.05).

Table 1: Univariate Analysis of PDAP (N=392).

Characteristics	No PDAP(N=323)	PDAP(N=69)	P
Age	49.42 ± 12.81	51.25 ± 11.06	0.228
Weigh	63.00 ± 11.60	63.44 ± 9.38	0.733
BMI	22.76 ± 3.84	22.74 ± 2.51	0.971
Dialysis duration	15.80 ± 19.52	18.94 ± 22.56	0.286
Dialysate bags/24hrs	**3.94 ± 0.78**	**4.38 ± 0.64**	**<.001**
Serum Calcium	2.15 ± 0.24	2.18 ± 0.28	0.467
Serum Phosphorus	1.90 ± 0.62	1.91 ± 0.60	0.885
Serum Potassium	**4.34 ± 0.79**	**3.83 ± 0.69**	**<.001**
Serum Albumin	**37.88 ± 5.41**	**34.30 ± 5.76**	**<.001**
iPTH	668.44 ± 534.83	668.27 ± 563.06	0.998
ALT	21.13 ± 12.29	18.25 ± 9.39	0.032
Cholinesterase	6656.36 ± 1275.65	6709.55 ± 1237.59	0.752
Triglyceride	1.93 ± 1.06	2.47 ± 1.78	0.019
Creatinine	683.71 ± 599.39	638.14 ± 543.43	0.536
SUA	432.31 ± 122.39	403.22 ± 106.83	0.068
BUN	22.82 ± 6.96	21.69 ± 6.39	0.217
SDS	54.45 ± 11.38	52.19 ± 13.76	0.207
SAS	46.03 ± 8.95	44.51 ± 8.69	0.198
CD-RISC	68.75 ± 24.29	71.93 ± 25.67	0.330
PSQI	7.80 ± 4.01	7.36 ± 3.92	0.413
MMSE	**27.33 ± 2.43**	**25.17 ± 2.84**	**<.001**
Hb	106.00 (96.00, 120.00)	105.00 (98.00, 120.00)	0.925
CRP	1.28 (0.50, 5.34)	1.12 (0.50, 5.34)	0.965
Alkaline phosphatase	88.80 (73.80, 126.35)	93.20 (73.40, 132.40)	0.997
Gender			
Male	191 (59.13)	43 (62.32)	0.624
Female	132 (40.87)	26 (37.68)	
Nation			
Han	321 (99.38)	69 (100.00)	1
Others	2 (0.62)	0 (0.00)	
Marital Status			
Unmarried	21 (6.50)	1 (1.45)	0.298
Married	285 (88.24)	65 (94.20)	
Divorced	13 (4.02)	3 (4.35)	
Bereaved	4 (1.24)	0 (0.00)	
Working Status			
Unemployed	202 (62.54)	42 (60.87)	0.213
Employed	64 (19.81)	10 (14.49)	
Retired	37 (11.46)	8 (11.59)	
Others	20 (6.19)	9 (13.04)	
Annual Income			

Table 1: Univariate Analysis of PDAP (N=392).

Characteristics	No PDAP(N=323)	PDAP(N=69)	P
≤ RMB 50,000	272 (84.21)	58 (84.06)	
RMB 50,000 to 150,000	43 (13.31)	9 (13.04)	0.243
RMB 150,000 to 300,000	6 (1.86)	0 (0.00)	
≥ RMB 300,000	2 (0.62)	2 (2.90)	
Education			
Primary school and below	**29 (8.98)**	**1 (1.45)**	
Junior high school	**149 (46.13)**	**27 (39.13)**	**0.007**
High school	**114 (35.29)**	**26 (37.68)**	
College and above	**31 (9.60)**	**15 (21.74)**	
Medical Insurance			
Rural medical insurance	133 (41.18)	27 (39.13)	
Employee Medical Insurance	182 (56.35)	42 (60.87)	0.373
Others	8 (2.48)	0 (0.00)	
Distance to PD Center			
≤1hr	147 (45.51)	29 (42.03)	
1-2hr	108 (33.44)	28 (40.58)	0.294
2-3hr	40 (12.38)	4 (5.80)	
≥3hr	28 (8.67)	8 (11.59)	
Residence			
Xuzhou	113 (34.98)	21 (30.43)	
Nantong	131 (40.56)	29 (42.03)	0.745
Yancheng	79 (24.46)	19 (27.54)	
Smoking			
Yes	10 (3.10)	2 (2.90)	0.931
No	313 (96.90)	67 (97.10)	
Keeping Pets			
Yes	53 (16.41)	13 (18.84)	0.624
No	270 (83.59)	56 (81.16)	
Method of Dialysis			
APD	99(30.65)	19(27.54)	
CAPD	202(62.54)	46(66.67)	0.809
IPD	22(6.81)	4(5.80)	
Dialysis Unit (Type of Tube)			
Tenckhoff straight tube	194 (60.06)	38 (55.07)	
Swan-neck straight tube	69 (21.36)	19 (27.54)	0.536
Swan-neck coil tube	60 (18.58)	12 (17.39)	
Operator			
Patient	307 (95.05)	61 (88.41)	0.070
Others	16 (4.95)	8 (11.59)	
Treatment			
Yes	55 (17.03)	15 (21.74)	0.354
No	268 (82.97)	54 (78.26)	
Pulmonary Infection			
Yes	5 (1.55)	1 (1.45)	0.952
No	318 (98.45)	68 (98.55)	
Intestinal Infection			
Yes	4 (1.24)	3 (4.35)	0.077
No	319 (98.76)	66 (95.65)	
Catheter and Tunnel Exit Infection			
Yes	**2 (0.62)**	**15 (21.74)**	**<.001**
No	**321 (99.38)**	**54 (78.26)**	
DM			
Yes	**35 (10.84)**	**20 (28.99)**	**<.001**
No	**288 (89.16)**	**49 (71.01)**	
CVD			
Yes	193 (59.75)	49 (71.01)	0.081
No	130 (40.25)	20 (28.99)	
CBVD			
Yes	12 (3.72)	4 (5.80)	0.428
No	311 (96.28)	65 (94.20)	
SLE			
Yes	5 (1.55)	1 (1.45)	1
No	318 (98.45)	68 (98.55)	
SHPT			
Yes	11 (3.41)	1 (1.45)	0.701
No	312 (96.59)	68 (98.55)	

Table 1: Univariate Analysis of PDAP (N=392).

Characteristics	No PDAP(N=323)	PDAP(N=69)	P
Pituitary Tumors			
Yes	3 (0.93)	1 (1.45)	0.541
No	320 (99.07)	68 (98.55)	
Anemia			
Yes	59 (18.27)	7 (10.14)	0.102
No	264 (81.73)	62 (89.86)	
Gout			
Yes	15 (4.64)	3 (4.35)	1
No	308 (95.36)	66 (95.65)	

Note.

P, for comparison between patients who had PDAP and who had not PDAP.

Abbreviations: BMI, body mass index; iPTH, intact parathyroxine; ALT, alanine aminotransferase; SUA, serum uric acid; BUN, blood urea nitrogen; SDS, self-rating depression scale; SAS, self-rating anxiety scale; CD-RISC, mental resilience scale; PSQI, Pittsburgh sleep quality index; MMSE, Mini-Mental State Examination; Hb, hemoglobin; CRP, C-reactive protein; APD, Automated Peritoneal Dialysis; CAPD, Continuous Ambulatory Peritoneal Dialysis; IPD, Intermittent Peritoneal Dialysis; DM, diabetes mellitus; CVD, Cardiovascular Disease; CBVD, Cerebrovascular Disease; SLE, Systemic Lupus Erythematosus; SHPT, Secondary Hyperparathyroidism.

Equilibrium Tests between Modeling Group and Verification Group

Three hundred ninety-two Parkinson's disease patients were randomly allocated to the modelling group (70%) and the verification group (30%). Equilibrium tests between the modelling group and the verification group indicate no statistically significant difference in baseline features ($p<0.05$).

Model Construction

Univariate Analysis of Incidence of PDAP in Modeling Group

Table 2 presents the findings of the univariate analysis about the incidence of PDAP in the modelling group. Patients in the modelling group who experienced PDAP exhibited a higher frequency of dialysate bags per 24 hours, reduced serum potassium levels, diminished serum albumin, elevated triglycerides, lower total MMSE scores, varying educational backgrounds, greater distances to the PD centre, and a higher incidence of intestinal infections, catheter and tunnel exit infections, and diabetes mellitus ($P<0.05$).

LASSO Analysis of Incidence of PDAP in Modeling Group

LASSO analysis was conducted on all independent variables, and the LASSO route coefficients are presented in Figure 1. The X-axis represents the logarithm of the penalty coefficient (log λ), while the Y-axis denotes the model regression coefficient. As log λ increases, the regression coefficient of each variable is progressively diminished and ultimately approaches 0.

Table 2: Univariate Analysis in Modeling Group (N=274).

Variable	No PDAP (n=225)	PDAP (N=49)	P
Age	49.77 ± 12.86	50.16 ± 11.30	0.843
Weigh	63.48 ± 11.52	64.71 ± 9.09	0.417
BMI	22.93 ± 3.89	23.04 ± 2.51	0.799
Dialysis duration	16.60 ± 20.29	21.73 ± 23.94	0.122
Dialysate bags/24hrs	**3.93 ± 0.80**	**4.33 ± 0.66**	**<.001**
Calcium	2.14 ± 0.24	2.20 ± 0.27	0.081
Phosphorus	1.91 ± 0.63	2.01 ± 0.64	0.162
Potassium	**4.38 ± 0.81**	**3.85 ± 0.74**	**<.001**
Albumin	**37.65 ± 5.45**	**34.62 ± 5.46**	**<.001**
iPTH	658.48 ± 533.31	645.59 ± 563.32	0.879
ALT	21.08 ± 12.41	18.33 ± 9.34	0.144
Cholinesterase	6699.49 ± 1302.85	6685.12 ± 1253.72	0.944
Triglyceride	**1.92 ± 1.06**	**2.56 ± 1.81**	**0.020**
Creatinine	734.74 ± 605.69	578.95 ± 570.68	0.101
SUA	435.18 ± 123.39	415.52 ± 101.83	0.299
BUN	23.13 ± 6.89	22.64 ± 6.62	0.651
SDS	54.60 ± 11.69	51.30 ± 14.52	0.142
SAS	46.15 ± 9.22	43.75 ± 8.23	0.094
CD-RISC	69.52 ± 23.47	72.24 ± 26.87	0.473
PSQI	7.97 ± 4.05	7.18 ± 4.01	0.217
MMSE	**27.44 ± 2.41**	**25.31 ± 2.90**	**<.001**
Hb	106.00 (93.00, 123.00)	105.00 (98.00, 119.00)	0.991
CRP	1.28 (0.50, 5.34)	1.12 (0.50, 5.65)	0.785
Alkaline phosphatase	88.80 (73.80, 126.60)	93.20 (73.40, 126.10)	0.938
Gender			
Male	139 (61.78)	32 (65.31)	0.644
Female	86 (38.22)	17 (34.69)	

Table 2: Univariate Analysis in Modeling Group (N=274).

Variable	No PDAP (n=225)	PDAP (N=49)	P
Nation			
Han	224 (99.56)	49 (100.00)	0.640
Others	1 (0.44)	0 (0.00)	
Marital Status			
Unmarried	17 (7.56)	1 (2.04)	
Married	197 (87.56)	45 (91.84)	0.424
Divorced	9 (4.00)	3 (6.12)	
Bereaved	2 (0.89)	0 (0.00)	
Working Status			
Unemployed	140 (62.22)	29 (59.18)	
Employed	45 (20.00)	5 (10.20)	0.080
Retired	27 (12.00)	8 (16.33)	
Others	13 (5.78)	7 (14.29)	
Annual income			
≤ RMB 50,000	184 (81.78)	42 (85.71)	
RMB 50,000 to 150,000	34 (15.11)	5 (10.20)	0.199
RMB 150,000 to 300,000	5 (2.22)	0 (0.00)	
≥ RMB 300,000	2 (0.89)	2 (4.08)	
Education			
Primary school and below	18 (8.00)	0 (0.00)	
Junior high school	113 (50.22)	18 (36.73)	**0.001**
High school	74 (32.89)	18 (36.73)	
College/Undergraduate	20 (8.89)	13 (26.53)	
Medical Insurance			
Rural medical insurance	92 (40.89)	17 (34.69)	
Employee Medical Insurance	126 (56.00)	32 (65.31)	0.284
Others	7 (3.11)	0 (0.00)	
Distance to PD Center			
≤1hr	107 (47.56)	17 (34.69)	
1-2hr	73 (32.44)	23 (46.94)	**0.046**
2-3hr	27 (12.00)	2 (4.08)	
≥3hr	18 (8.00)	7 (14.29)	
Residence			
Xuzhou	82 (36.44)	11 (22.45)	
Nantong	85 (37.78)	21 (42.86)	0.153
Yancheng	58 (25.78)	17 (34.69)	
Smoking			
Yes	8 (3.56)	2 (4.08)	0.859
No	217 (96.44)	47 (95.92)	
Keeping pets			
Yes	39 (17.33)	10 (20.41)	0.611
No	186 (82.67)	39 (79.59)	
Method of Dialysis			
APD	72(32.00)	13(26.53)	
CAPD	135(60.00)	34(69.39)	0.405
IPD	18(8.00)	2(4.08)	
Dialysis Unit (Type of Tube)			
Tenckhoff straight tube	129 (57.33)	28 (57.14)	
Swan-neck straight tube	53 (23.56)	13 (26.53)	0.854
Swan-neck coil tube	43 (19.11)	8 (16.33)	
Operator			
Patient	214 (95.11)	44 (89.80)	0.150
Others	11 (4.89)	5 (10.20)	
Treatment			
Yes	34 (15.11)	11 (22.45)	0.209
No	191 (84.89)	38 (77.55)	
Pulmonary Infection			
Yes	2(0.89)	1(2.04)	0.483
No	223(99.11)	48(97.96)	
Intestinal Infection			
Yes	3(1.33)	3(6.12)	**0.038**
No	222(98.67)	46(93.88)	
Catheter and Tunnel Exit Infection			
Yes	2(0.89)	9(18.37)	**<.001**
No	223(99.11)	40(81.63)	
DM			

Table 2: Univariate Analysis in Modeling Group (N=274).

Variable	No PDAP (n=225)	PDAP (N=49)	P
Yes	26 (11.56)	13 (26.53)	**0.007**
No	199 (88.44)	36 (73.47)	
CVD			
Yes	140 (62.22)	35 (71.43)	0.224
No	85 (37.78)	14 (28.57)	
CBVD			
Yes	6 (2.67)	3 (6.12)	0.219
No	219 (97.33)	46 (93.88)	
SLE			
Yes	2 (0.89)	1 (2.04)	0.483
No	223 (99.11)	48 (97.96)	
SHPT			
Yes	8 (3.56)	1 (2.04)	0.590
No	217 (96.44)	48 (97.96)	
Pituitary Tumors			
Yes	1 (0.44)	1 (2.04)	0.326
No	224 (99.56)	48 (97.96)	
Anemia			
Yes	43 (19.11)	6 (12.24)	0.256
No	182 (80.89)	43 (87.76)	
Gout			
Yes	11 (4.89)	3 (6.12)	1
No	214 (95.11)	46 (93.88)	

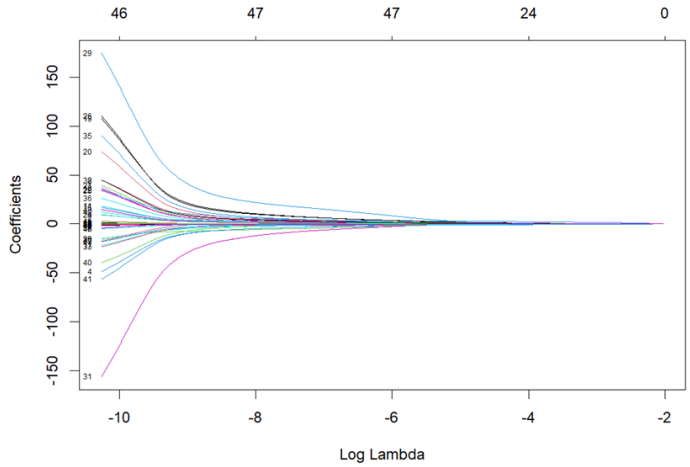

Figure 1: LASSO Analysis of Fold Cross-Validation.

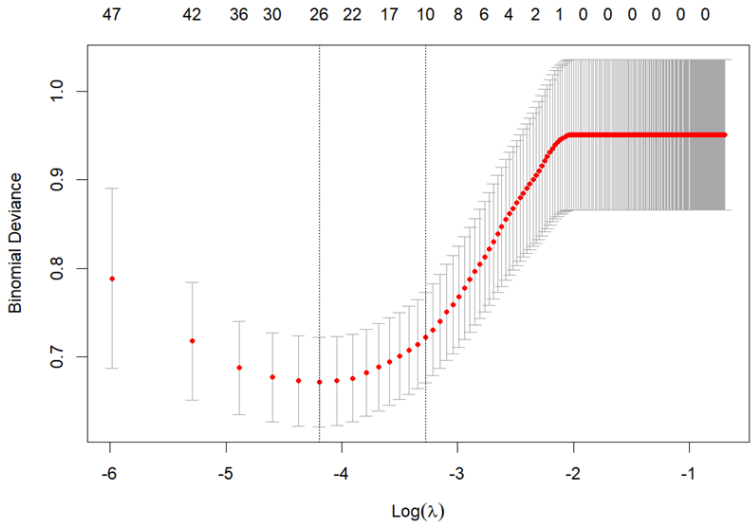

Figure 2: LASSO Analysis of Coefficient Profiles.

Figure 2 illustrates the cross-validation curve for the LASSO analysis. The X-axis represents logλ, while the Y-axis denotes the deviation of the binomial distribution. A lower Y-axis value indicates a superior model fit to the data. When λ=lambda.1se = 0.0377, ten potential predictors were identified, associated with PDAP, including dialysis duration, serum potassium, serum albumin, triglycerides, dialysate bags per 24 hours, intestinal infection, catheter and tunnel exit infection, diabetes mellitus, educational background, and total score of the MMSE.

Logistic Regression Analysis of Incidence of PDAP in Modeling Group

Table 3 shows that serum potassium, serum albumin, triglyceride, total score of MMSE, patients with catheter and tunnel exit infection and DM was risk factors for incidence of PDAP (P<0.05).

Table 3: Logistic Regression Analysis(n=274).

Risk Factors	β	SE	Z	P	OR	95%CI
Serum Potassium	-0.900	0.280	-3.216	0.001	0.407	0.235-0.704
Serum Albumin	-0.117	0.038	-3.097	0.002	0.890	0.827-0.958
Triglyceride	0.502	0.144	3.486	<.001	1.653	1.246-2.192
MMSE	-0.301	0.078	-3.859	<.001	0.740	0.635-0.862
Catheter and Tunnel Exit Infection	3.862	0.968	3.989	<.001	47.552	7.130-317.112
DM	1.086	0.498	2.180	0.029	2.961	1.116-7.861
Constant	12.786	2.667	4.795	<.001	357220.675	

Note.
"0" means "No", "1" means "Yes"

According to the results of table 1 to 3, the CPMs of incidence of PDAP was constructed as follows:
Logit(P) = 12.786 – 0.900 * serum potassium - 0.117 * serum albumin + 0.502 * triglyceride – 0.301 * total score of MMSE + 3.862 * catheter and tunnel exit infection + 1.086 * DM

Model Verification

ROC Curve of CPMs of PDAP

Table 4 indicates that the Area under Curve (AUC) for the modelling group was 0.856, with a sensitivity of 0.867 and a specificity of 0.776, implying that the CPMs of PDAP exhibited strong distinction (Figure 3). The validation group's AUC was 0.863, with a sensitivity of 0.867 and a specificity of 0.800, confirming that the CPMs of PDAP exhibited strong distinction (Figure 4).

Table 4: Differentiation Test of CPMs of PDAP.

Data Group	AUC (95%CI)	Accuracy (95%CI)	Sensitivity (95%CI)	Specificity (95%CI)
Modeling Group	0.856 (0.784-0.927)	0.850 (0.803-0.890)	0.867 (0.822-0.911)	0.776 (0.659-0.892)
Validation Group	0.863 (0.752-0.973)	0.856 (0.779-0.914)	0.867 (0.800-0.935)	0.800 (0.625-0.975)

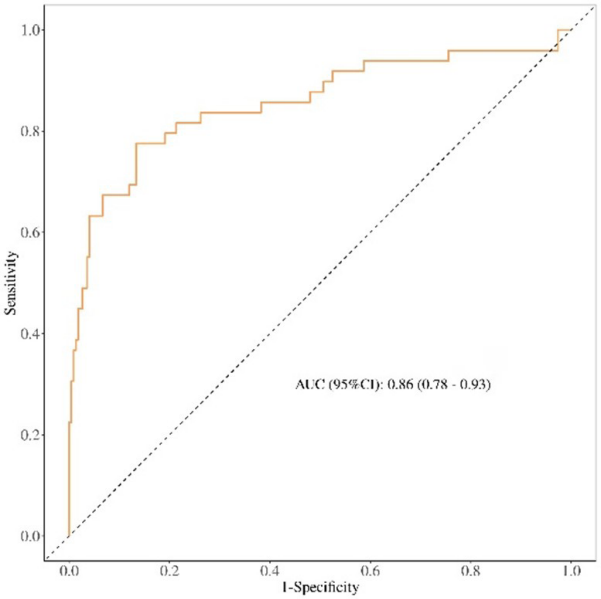

Figure 3: ROC of Modeling Group.

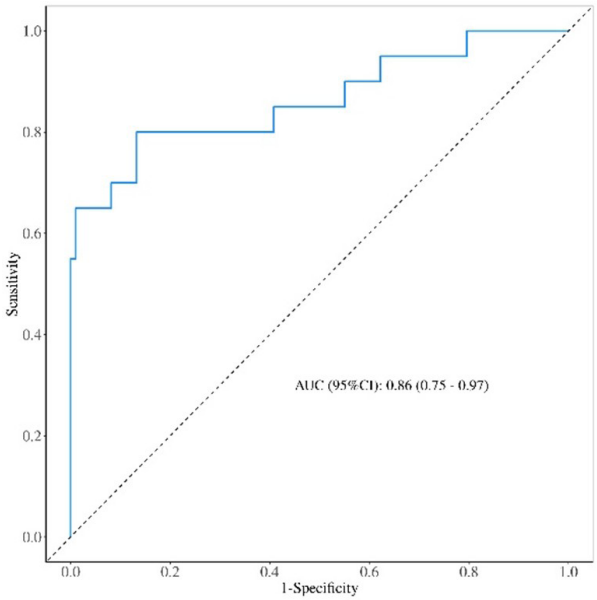

Figure 4: ROC of Verification Group.

Calibration Curve and Hosmer-Lemeshow(H-L) Test for CPMs of PDAP

The calibration curve showed that the actual values of the modeling group and the verification group fitted well with the predicted values (Figure 5-6). The H-L test of modeling group $\chi2 = -22.073$, df = 8, P = 1.000. Verification group H-L test $\chi2 = 3.820$, df = 8, P = 0.873.

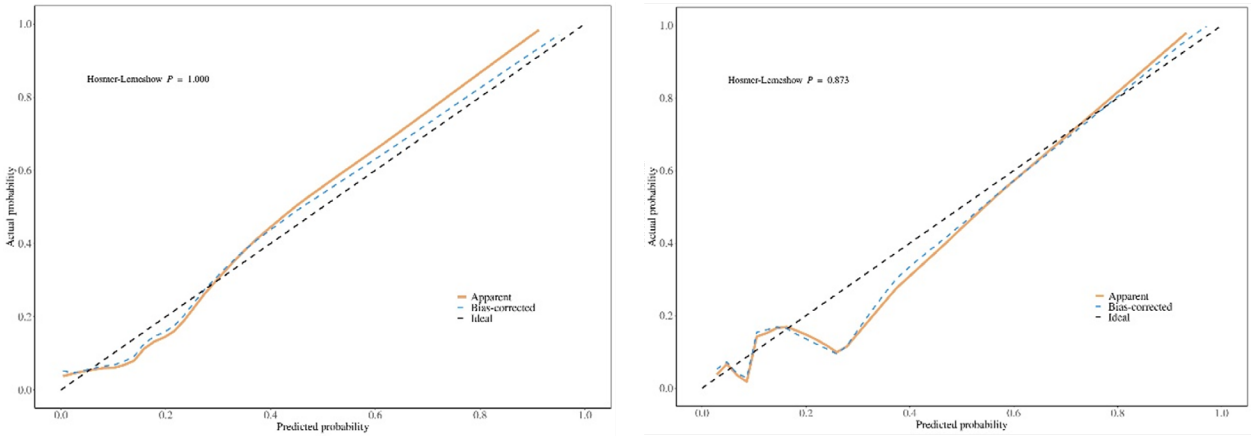

Figure 5-6: Calibration Curve of Modeling Group and Verification Group.

Clinical Efficacy of CPMs of PDAP

Figure 7-8 illustrates that the decision curve analysis (DCA) for the modelling group indicates a threshold ranging from 5% to 92%, with the DCA curve positioned above the reference line, signifying that the decision curve possesses substantial clinical applicability. The DCA for the validation group indicates a threshold ranging from 5% to 98%, with the DCA curve positioned in the top right quadrant relative to the reference line, signifying that the decision curve possesses substantial clinical applicability.

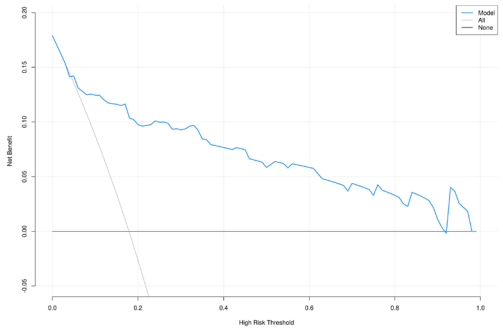

Figure 7: DCA of Modeling Group.

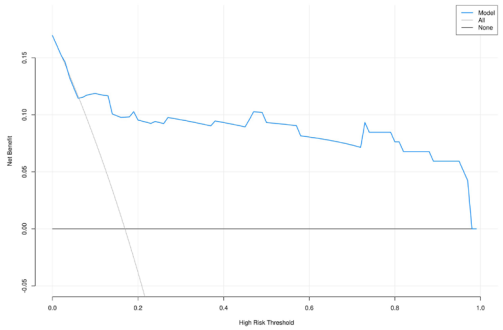

Figure 8: DCA of Verification Group.

Model Visualization

The nomogram model results indicated that in PD patients with catheter and tunnel exit infections, the model increased by 100 points; in PD patients with diabetes mellitus, the model increased by 28 points; a decrease of 0.5 mmol/L in serum potassium resulted in a 10-point increase in the curve model; for each 2 g/L reduction in serum albumin, the nomogram model increased by 5 points; a 0.5 mmol/L rise in triglycerides led to a 5-point increase in the nomogram model; and a 1-point decline in the MMSE score corresponded to a 6-point increase in the nomogram model. In the nomogram, each influencing factor is represented by a vertical line that aligns with the upper scale, indicating the individual score of the factor. The aggregate of individual scores for each contributing element constitutes the overall score, which aligns with the lower scale representing the risk likelihood of PDAP in patients with Parkinson's Disease. The CPMs of PDAP, derived from six factors—serum potassium, serum albumin, triglycerides, MMSE score, PD patients with catheter and tunnel exit infection, and diabetes mellitus—can effectively predict the likelihood of PDAP.

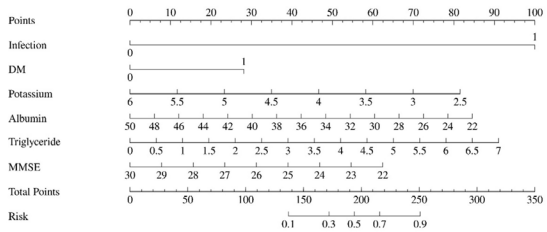

Figure 9: Nomogram of CPMs of PDAP.

In the case of a non-diabetic patient with a catheter and tunnel exit infection, presenting with a serum potassium level of 5.5, serum albumin of 46, triglycerides at 2.4,

and a Mini-Mental State Examination (MMSE) score of 22, the total score can be calculated as 100 + 0 + 10 + 10 + 30 + 60 = 210 points according to the nomogram, indicating a probability of PDAP of approximately 70%.

Discussing

The occurrence of PDAP in this study was 0.31 occurrences per patient per year. This result aligned with the global average incidence of peritonitis documented in the literature at 0.30 episodes per patient per year,[11] although it significantly exceeded the 0.175-0.198 episodes per patient per year recorded in China.[12] The prevalence of PDAP has diminished worldwide over time. A systematic evaluation of data including 81 nations revealed that the incidence of peritonitis in PDAP has declined from 0.600 episodes per patient per year in 1992 to 0.303 episodes per patient per year in 2019.[13] The findings from Renji Hospital, affiliated with Shanghai Jiao Tong University in China, indicated that the incidence of peritonitis at the centre declined from 0.214 episodes per patient per year in 2004 to 0.160 episodes per patient per year in 2015.[14] Currently, there are no official reports regarding the incidence of PDAP in Jiangsu Province. Zhang Yi et al.'s work including 183 PD patients at Yangzhou Central Hospital revealed a total infection incidence of PDAP of 2.19%.[15] Li Guizhen's analysis and research involving 7,830 patients across four hospitals in Nanjing revealed that among 3,528 individuals with PDAP, there were a total of 7,506 instances of PDAP within one year.[16] Although the mortality rate of peritonitis is less than 5%, peritonitis remains one of the main causes of death for PD patients, accounting for approximately 16%.[17] Huadu District People's Hospital in Guangzhou is a district-level hospital. It has applied the "4R Theory of Crisis Management" to the management of peritonitis in PD patients in the hospital. The "4R Theory of Crisis Management" was first proposed by Robert Hirsch and consists of four modules: reduction, readiness, response, and recovery. The incidence of peritonitis in PD patients without using the "4R Theory of Crisis Management" is 0.26 times per patient year, which meets the requirements of the ISPD guidelines, but still has room for improvement compared to large PD centers in China; the incidence of peritonitis in PD patients intervened with the "4R Theory of Crisis Management" is 0.12 times per patient year, which is close to the level of excellent PD centers at home and abroad.[18]

The currently utilised CPMs mostly consist of three groups. The initial group comprises traditional CPMs predominantly grounded in regression analysis, including logistic regression and Cox proportional hazards models. These models are beneficial due to their robust interpretability, offering explicit variable weights and risk ratios (e.g., odds ratios or hazard ratios), which enhance comprehension and application by clinicians.[19] Moreover, conventional statistical models necessitate very modest sample sizes, rendering them appropriate for research with constrained data, and they exhibit strong performance in managing linear connections.[20] However, they generally presume linear correlations among variables, but clinical data can encompass intricate nonlinear interactions.[21] Moreover, conventional models exhibit sensitivity to absent data, frequently necessitating complete datasets or repeated imputation techniques, hence augmenting analytical complexity.[22] In clinical practice, these models are adept for risk stratification and prognostic evaluation. The second group comprises machine learning (ML) models, including random forests and support vector machines (SVM), which have robust efficacy in clinical prediction. These models are capable of processing high-dimensional data, such as genomics or imaging data, and can autonomously identify nonlinear correlations and interactions.[23] Moreover, machine learning models have enhanced resilience to absent data and may autonomously manage missing values via algorithms. Machine learning algorithms generally necessitate extensive training datasets and may exhibit overfitting in clinical investigations characterised by limited sample sizes.[24] In clinical practice, machine learning is ideally suited for applications like medical imaging diagnostics and precision medicine; yet, its deployment necessitates integration with clinical validation and interpretability tools, such as SHAP values. The third group comprises hybrid models that seek to reconcile interpretability with predictive performance. Hybrid models has the advantage of combining the high accuracy of machine learning with enhanced interpretability via reduced model architecture.[25] Nonetheless, the development of hybrid models entails increased complexity and necessitates interdisciplinary collaboration among statisticians, doctors, and computer scientists.[13] Furthermore, their efficacy may be constrained by data quality concerns. In clinical practice, hybrid models are especially appropriate for dynamic prediction contexts. This study employed a standard clinical prediction model due to the impact of parameters like sample size and research duration.

The findings of this study indicated that blood potassium, serum albumin, triglycerides, catheter and tunnel exit infections, diabetes mellitus, and the overall score of the MMSE were risk factors for the occurrence of PDAP, and the CPMs for PDAP were effectively created, verified, and visualised. Currently, there is a paucity of research on the development of Clinical Pathways Models (CPMs) pertaining to peritonitis in patients undergoing Peritoneal Dialysis (PD), and no studies align with the findings of this investigation. Sapsitthikul *et al.*[26] performed a prospective cohort study with 546 PD patients, demonstrating that enhancing home visits via machine learning (ML) could avert the incidence of PDAP. Yan *et al.*[27] shown that CRP, serum albumin, diabetes mellitus, peritoneal dialysis course, and pathogen type were risk factors for refractory peritonitis in patients undergoing peritoneal dialysis, and successfully created and validated a nomogram to predict refractory peritoneal dialysis-related peritonitis. Zang *et*

al.[28] employed five machine learning algorithms—random forest (RF), least absolute shrinkage and selection operator (LASSO), decision tree, K-nearest neighbour (KNN), and logistic regression (LR)—to construct a clinical prediction model for technical failure in patients with PDAP. The results indicated that the RF prediction model could precisely forecast the technical failure in PDAP patients. A multicenter retrospective cohort study in Thailand created a multivariate logistic regression method to predict the likelihood of peritoneal-related technical failure.[19] Meng *et al.*[30] developed a nomogram to forecast the resolution of peritonitis in patients with PDAP utilising multivariable logistic regression. The predictive modal graph model, while intuitive and relevant to clinical practice, has a c statistic value of 0.756.[30] The remaining two single-center studies only employed LR analysis to construct prediction models and lacked independent datasets to validate their predictive efficacy.[31] A retrospective analysis was conducted on clinical data from 376 patients indicated that 8 factors could predict the risk of the incidence of PDAP, which including age, dialysis duration, albumin, hemoglobin, β2-microglobulin, potassium and lymphocyte count.[32] Based on the CPMs for PDAP, we can implement targeted interventions for patients at high risk of PDAP. The Continuous Quality Improvement (CQI) program was proposed by Dr. Deming in the 1950s as an enterprise management concept. It mainly consists of four-step cycles, namely the PDCA cycle (Plan-Do-Check-Act).[33] The "ISPD Peritonitis Guidelines Recommendations: 2022 Updates on Prevention and Treatment"[34] recommends that as part of the CQI program, all PD centers should regularly monitor the incidence of peritonitis.Given the special nature of home-based PD, which is mostly performed by patients themselves, addressing the issues of unstandardized management, education, and follow-up for home-based PD patients, as well as alleviating the problem of difficult dialysis for patients in remote and rural areas, can be achieved by using an intelligent diagnosis and treatment full-process management platform for high-risk patients who are not hospitalized. This platform enables patients to enjoy convenient, efficient, continuous, and high-quality intelligent PD management services, thereby significantly improving the prognosis and quality of life of patients.[35] In conclusion, various machine learning techniques can yield models with distinct predictive outcomes. At now, no study exists that can consistently construct clinical prediction models for peritoneal dialysis-related peritonitis. Secondly, the predictive models developed through various construction methodologies, regional contexts, and incorporated variables exhibit significant variability, rendering the current models unsuitable for widespread application.

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Authors' Contributions

Prof. Sairah Abdul Karim designed, guided and supervised the development and quality of the project;
Guo Lingling project design, data gathering, statistical analysis, and authorship of the paper.
Qian Hailan, Shen YuanYuan, Qian WeiWei, Liu Yin, Xu Min, Li Na participated in the data collection.
All authors read the paper and agreed with the final content.

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Data and Material Accessibility

All data collected or evaluated throughout this research are encapsulated within the present document. For additional information, please contact the corresponding author.

Declarations

Ethical Considerations and Participation Agreement

Adhering to the principles outlined in the Declaration of Helsinki, this investigation was sanctioned by the Ethics Committee at Yancheng Third People's Hospital. Each participant provided written consent for their involvement.

Publication Approval

Not relevant.

Conflict of Interest Disclosure

The authors affirm that they have no conflicts of interest to disclose.

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