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Sexual Dysfunction Risk Assessment in Peritoneal Dialysis: A Machine Learning Study

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Abstract

Background: Sexual dysfunction (SD) is a common yet underrecognized complication in patients receiving peritoneal dialysis (PD). We investigated the prevalence of SD and its associated factors, and developed interpretable machine learning models to predict SD risk in PD patients.

Methods: We enrolled 209 PD patients (100 males, 109 females) in this retrospective cross-sectional study. Sexual function was assessed with the International Index of Erectile Function-5 (IIEF-5) in males and the Female Sexual Function Index (FSFI) in females. We collected demographic, clinical, biochemical, and psychosocial variables, and performed univariate analysis, Spearman correlation, and multivariate linear and logistic regression. Eight machine learning algorithms were compared. SHapley Additive exPlanations (SHAP) were applied to interpret the best-performing model.

Results: The overall prevalence of SD was 77.5% (162/209), with rates of 78.0% (78/100) in males and 77.1% (84/109) in females. Multivariate analysis identified depression score (SDS; $\beta = -0.24$, $P = 0.013$), residual renal function ($\beta = +0.005$, $P = 0.021$), marital status ($\beta = +8.77$, $P = 0.0003$), and α -blocker use ($\beta = -4.14$, $P = 0.013$) as independent predictors of male erectile function. In-sample AUCs from logistic regression were 0.808, 0.860, and 0.850 for overall SD, male ED, and female FSD, while corresponding test-set AUCs were 0.772, 0.672, and 0.541. Among machine learning models, CatBoost produced the highest test-set AUC (0.808), and the ensemble model (Random Forest + XGBoost) offered the best balance of sensitivity and specificity (AUC = 0.801). SHAP analysis identified SDS as the dominant predictor (mean |SHAP| = 0.0455), followed by residual renal function (0.0291), β 2-microglobulin (0.0234), and hemoglobin (0.0223). Subgroup analyses indicated that psychosocial factors were more prominent in younger patients (≤ 40 years), while physiological parameters carried greater weight in older patients (> 40 years).

Conclusions: Sexual dysfunction is highly prevalent among PD patients. Depression is the strongest modifiable risk factor; residual renal function is an important protective factor. Machine learning models may help predict individual risk and guide clinical decisions.

Keywords: Peritoneal dialysis; Sexual dysfunction; Machine learning; SHAP; Depression; Residual renal function

1 Introduction

Chronic kidney disease (CKD) affects approximately 9.1% of the global population and is a major public health burden¹. As CKD advances to end-stage renal disease (ESRD), renal replacement therapy becomes necessary. Peritoneal dialysis (PD) offers several advantages: it is home-based, preserves residual renal function (RRF) more effectively than hemodialysis, and is associated with better quality of life in selected patients².

As dialysis technology has extended patient survival, attention has shifted toward quality of life. Sexual dysfunction (SD) is a common yet underrecognized complication in CKD and dialysis populations. Reported prevalence of erectile dysfunction (ED) in male dialysis patients ranges from 50% to 90%; female sexual dysfunction (FSD) affects 40% to 80% of women on dialysis³. SD remains underdiagnosed and undertreated, partly because patients feel embarrassed and clinicians are uncomfortable discussing it³. The etiology of SD in PD patients is multifactorial. Contributing factors include hormonal disturbances (hypogonadism, hyperprolactinemia), vascular disease, neuropathy, psychological factors (depression, anxiety), medication side effects, and socioeconomic factors^{3,4}. Among these, depression is a strong predictor. Several studies have found significant associations between depressive symptoms and impaired sexual function in CKD populations^{5,6}.

Traditional statistical methods such as logistic regression have been widely used to

identify risk factors for SD. However, these approaches may be limited in capturing complex, non-linear interactions between variables⁷. Machine learning (ML) algorithms, including ensemble methods and gradient boosting, may capture complex patterns in high-dimensional data that linear models miss⁸. The integration of explainable artificial intelligence (XAI) tools, particularly SHapley Additive exPlanations (SHAP), has made ML models more interpretable and useful in clinical practice⁹.

No prior study has combined multiple ML algorithms with SHAP-based explainability to predict SD risk in PD patients. Accordingly, we examined the prevalence of SD in a single-center PD cohort, identified independent risk factors via conventional regression, compared several ML models for predictive performance, and applied SHAP analysis to render model outputs clinically interpretable.

2 Materials and Methods

2.1 Study Design and Participants

This retrospective cross-sectional study was conducted using data from patients who underwent PD between January 2023 and April 2025. Inclusion criteria were: (1) age ≥ 18 years; (2) PD duration ≥ 3 months; (3) ability to provide informed consent. Exclusion criteria included: (1) severe cognitive impairment precluding questionnaire completion; (2) active peritonitis within the preceding 3 months; (3) malignancy with life expectancy < 6 months. The study protocol was approved by the Institutional Ethics Committee (Approval No. :2026-052-01). All participants provided written informed consent prior to enrollment.

2.2 Data Collection

2.2.1 Demographic and Clinical Variables

The following data were extracted from electronic medical records: age, sex, marital status, education level, monthly income, body mass index (BMI), dialysis modality (continuous

ambulatory peritoneal dialysis [CAPD], automated peritoneal dialysis [APD], or combined peritoneal dialysis and hemodialysis [PHD]), comorbidities (hypertension, diabetes mellitus), and medications (calcium channel blockers, angiotensin receptor blockers, angiotensin-converting enzyme inhibitors, α -blockers, β -blockers).

2.2.2 Biochemical Parameters

Blood samples were collected during routine outpatient visits. Assessed parameters included serum creatinine, blood urea nitrogen (BUN), Kt/V, creatinine clearance (Ccr), hemoglobin (Hb), albumin, prealbumin, calcium, phosphorus, potassium, parathyroid hormone (PTH), brain natriuretic peptide (BNP), C-reactive protein (CRP), β 2-microglobulin (β 2-MG), 4-hour peritoneal equilibration test (PET) D/P creatinine ratio, and residual renal function (RRF; originally recorded in mL/24h).

2.2.3 Psychological Assessment

Depression and anxiety were evaluated using the Zung Self-Rating Depression Scale (SDS) and the Zung Self-Rating Anxiety Scale (SAS), respectively¹⁰. SDS scores ≥ 50 and ≥ 60 indicated mild and moderate-to-severe depression, respectively. SAS scores ≥ 50 indicated anxiety.

2.2.4 Sexual Function Assessment

Male sexual function was assessed using the 5-item International Index of Erectile Function (IIEF-5), a validated instrument with scores ranging from 1 to 25¹¹. A score ≤ 21 was used to define ED¹¹. Female sexual function was evaluated using the Female Sexual Function Index (FSFI), a 19-item questionnaire covering six domains (desire, arousal, lubrication, orgasm, satisfaction, and pain)¹². In this study, corrected FSFI scores < 25 were classified as FSD, consistent with established cutoffs¹³.

2.3 Outcome Definitions

Three binary outcomes were defined: Male ED: IIEF-5 ≤ 21 (positive) vs. >21 (negative); Female FSD: Corrected FSFI <25 (positive) vs. ≥ 25 (negative); Overall SD: Positive if either male ED or female FSD was present.

2.4 Statistical Analysis

Normality was assessed using the Shapiro-Wilk test. Normally distributed continuous variables were expressed as mean $\pm$ standard deviation (SD) and compared using independent-samples t-tests. Non-normally distributed variables were presented as median (interquartile range [IQR]) and compared using the Mann-Whitney U test. Categorical variables were expressed as frequencies (percentages) and compared using χ^2 or Fisher's exact tests.

Spearman rank correlation was used to assess associations between continuous variables. Multivariate linear regression was applied for continuous outcomes (IIEF-5 and FSFI scores), and multivariate logistic regression was used for binary outcomes. Odds ratios (ORs) with 95% confidence intervals (CIs) were reported. The variance inflation factor (VIF) was calculated to assess multicollinearity; values >10 were considered indicative of significant collinearity.

All statistical analyses were performed using Python (Version number 3.11). A two-sided $P < 0.05$ was considered statistically significant.

2.5 Machine Learning Modeling

2.5.1 Feature Engineering and Data Splitting

A total of 21 candidate features were selected based on clinical relevance and univariate screening:

10 continuous variables (age, BMI, Hb, albumin, BNP, β_2 -MG, RRF, D/Pcr, SDS, SAS) and 11 categorical variables (sex, marital status, education, income, dialysis modality, hypertension,

diabetes, CCB, ARB, β -blocker, ACEI). Missing values in continuous variables were imputed using the median; categorical missing values were imputed using the mode. The dataset was split into training (80%) and testing (20%) sets using stratified random sampling to preserve the distribution of sex and outcome.

2.5.2 Model Evaluation

Model performance was evaluated on the held-out test set using: area under the receiver operating characteristic curve (AUC-ROC), accuracy, sensitivity, specificity, F1-score, positive predictive value (PPV), negative predictive value (NPV), and Youden index. Five-fold stratified cross-validation (CV) was used to assess generalization performance. The optimal classification threshold was determined by maximizing the Youden index¹⁴.

2.5.3 Explainability Analysis

SHAP values were computed for the Random Forest model (selected for its stability, well-established interpretability, and balanced performance across metrics) to quantify each feature's contribution to individual predictions⁹. Global interpretability was visualized using SHAP summary plots, and feature-specific relationships were explored using SHAP dependence plots for the top four predictors.

2.6 Subgroup and Sensitivity Analyses

Subgroup analyses were performed stratified by sex, age (≤ 40 vs. > 40 years), dialysis modality (CAPD vs. non-CAPD), and depression status (SDS < 50 vs. ≥ 50). Sensitivity analyses examined the robustness of findings under different missing data strategies (median imputation, complete-case analysis, zero imputation) and after excluding high-VIF variables.

3 Results

3.1 Patient Characteristics and Prevalence of Sexual Dysfunction

A total of 209 PD patients were enrolled, comprising 100 males (47.8%) and 109 females (52.2%). The patient selection flowchart is shown in Figure 1. The median age was 41 years (IQR: 32–50). CAPD was the predominant modality (72.7%), followed by APD (18.2%) and combined PD and hemodialysis (PHD, 9.1%). Hypertension and diabetes were present in 78.0% and 28.2% of patients, respectively.

The overall prevalence of SD was 77.5% (162/209). Male ED occurred in 78.0% (78/100), and female FSD in 77.1% (84/109). No significant gender difference in SD prevalence was observed ($P = 0.87$). Figure 2 illustrates the prevalence by gender and age group.

Figure 1 CONSORT Flow Diagram

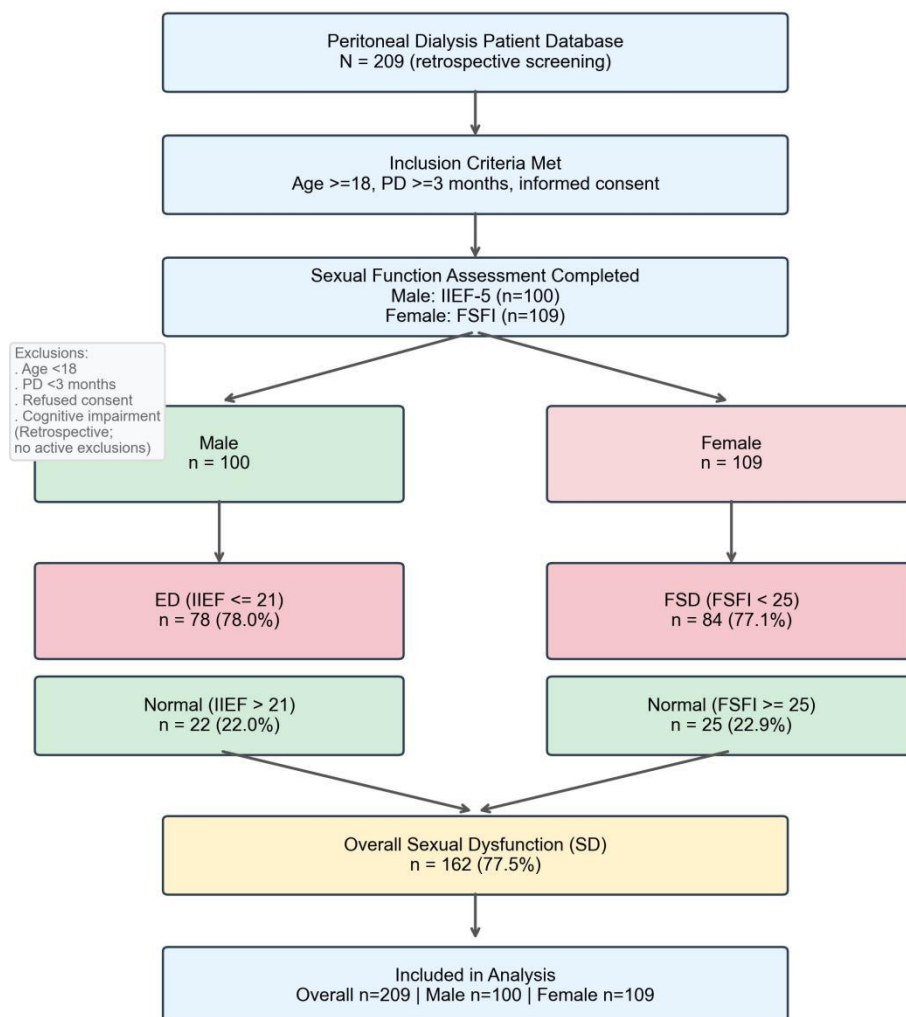


Figure 1: CONSORT flow diagram of patient selection and analysis.

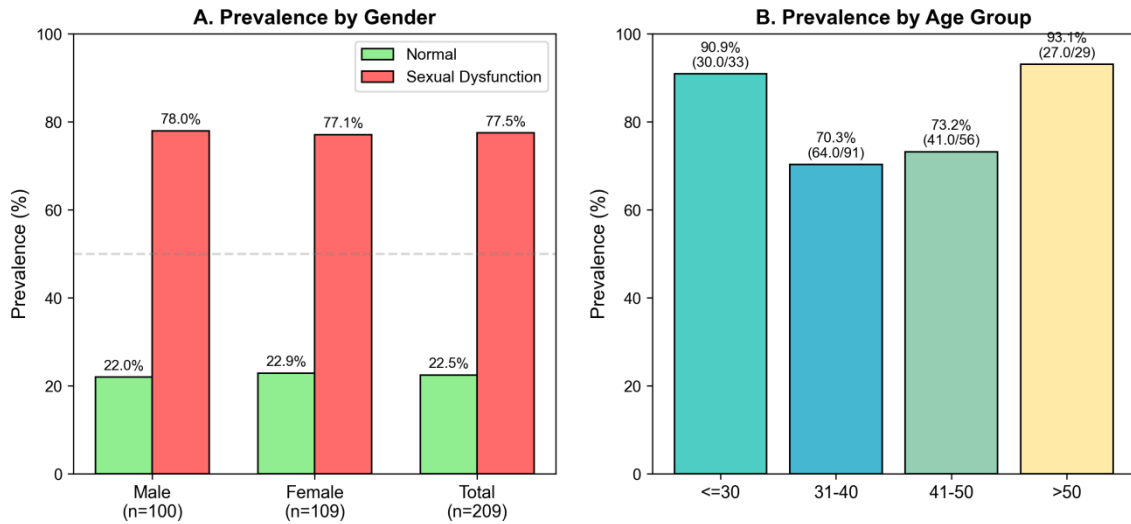


Figure 2: Prevalence of sexual dysfunction. (A) By gender; (B) By age group.

3.2 Scale Score Distributions

The median IIEF-5 score among males was 17.0 (IQR: 9.8–21.0), with a left-skewed distribution. The median corrected FSFI score among females was 17.2 (IQR: 6.2–23.8). Median SDS and SAS scores were 41 (IQR: 34–47) and 36 (IQR: 32–39), respectively (Figure 3).

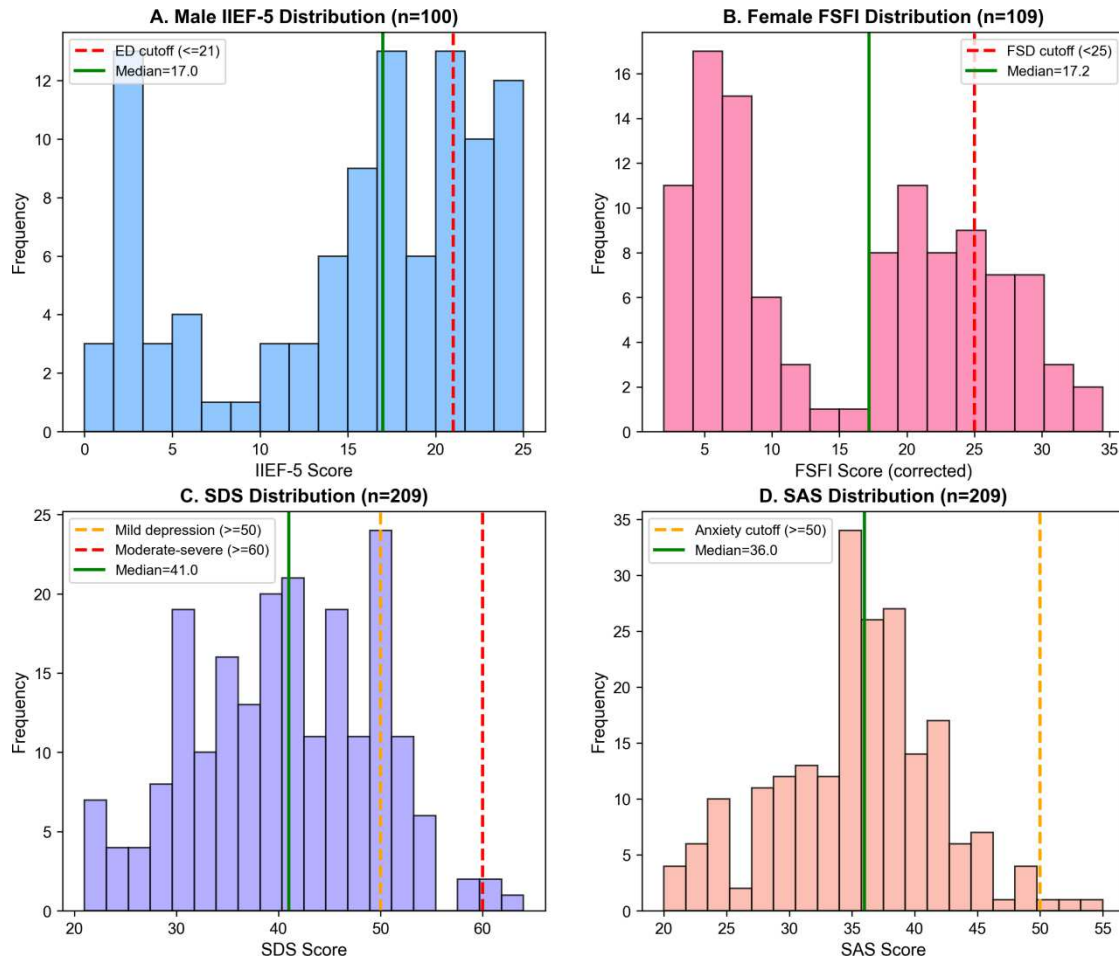


Figure 3: Distribution of questionnaire scores. (A) Male IIEF-5; (B) Female FSFI (corrected); (C) SDS; (D) SAS. Dashed lines indicate clinical cutoffs.

3.3 Univariate Analysis

Comparisons between patients with and without SD revealed significant differences in multiple domains (Table 1). Patients with SD had lower Ccr, lower hemoglobin, higher SDS scores, lower RRF, and higher β 2-MG levels (all $P < 0.05$). Marital status, monthly income, and depression severity also differed significantly between groups. Beta-blocker use showed a marginally significant association ($P = 0.087$).

Table 1: Baseline characteristics by overall sexual dysfunction status

Variable	No SD (<i>n</i> =47)	SD (<i>n</i> =162)	<i>P</i> value
Age, years	38 (31–48)	42 (33–51)	0.11
Male sex, <i>n</i> (%)	22 (46.8)	78 (48.1)	0.87
BMI, kg/m ²	22.5 (20.3–25.1)	22.8 (20.5–25.4)	0.72
Ccr, mL/min	66.1 (57.6–92.4)	59.5 (47.1–79.0)	0.025
Hemoglobin, g/L	117.6±19.5	110.0±19.7	0.021
Albumin, g/L	39.2 (36.1–41.8)	38.0 (34.8–40.9)	0.14
RRF, mL/24h ^a	802.5 (325.0–1222.5)	400.0 (0.0–860.0)	0.002
β ₂ -MG, mg/L	24.0 (20.0–31.1)	29.0 (23.0–35.2)	0.027
SDS score	37.1±9.0	41.6±8.7	0.002
SAS score	34.0 (31.0–38.5)	37.0 (32.0–40.0)	0.052
Married, <i>n</i> (%)	38 (80.9)	108 (66.7)	0.042
Low income ^b , <i>n</i> (%)	28 (59.6)	119 (73.5)	0.037
Beta-blocker use, <i>n</i> (%)	18 (38.3)	78 (48.1)	0.087

a RRF unit as originally recorded (mL/24h). b Low income defined as monthly income ≤5000 CNY. Note: Continuous variables are presented as median (IQR) or mean±SD; categorical variables as *n* (%). Abbreviations: SD = standard deviation; IQR = interquartile range; Ccr = creatinine clearance; RRF = residual renal function; SDS = Self-Rating Depression Scale; SAS = Self-Rating Anxiety Scale.

3.4 Correlation Analysis

Spearman correlation analysis revealed a moderate negative correlation between male IIEF-5 and SDS scores ($r=-0.33$, $P = 0.0008$). Residual renal function correlated positively with

IIEF-5 ($r=+0.35$, $P = 0.0005$), while $\beta 2$ -MG correlated negatively ($r=-0.21$, $P = 0.044$). In females, FSFI showed marginal positive correlation with hemoglobin ($r=+0.18$, $P = 0.067$) and marginal negative correlation with BNP ($r=-0.19$, $P = 0.092$). The correlation matrix for key variables is presented in Figure 4.

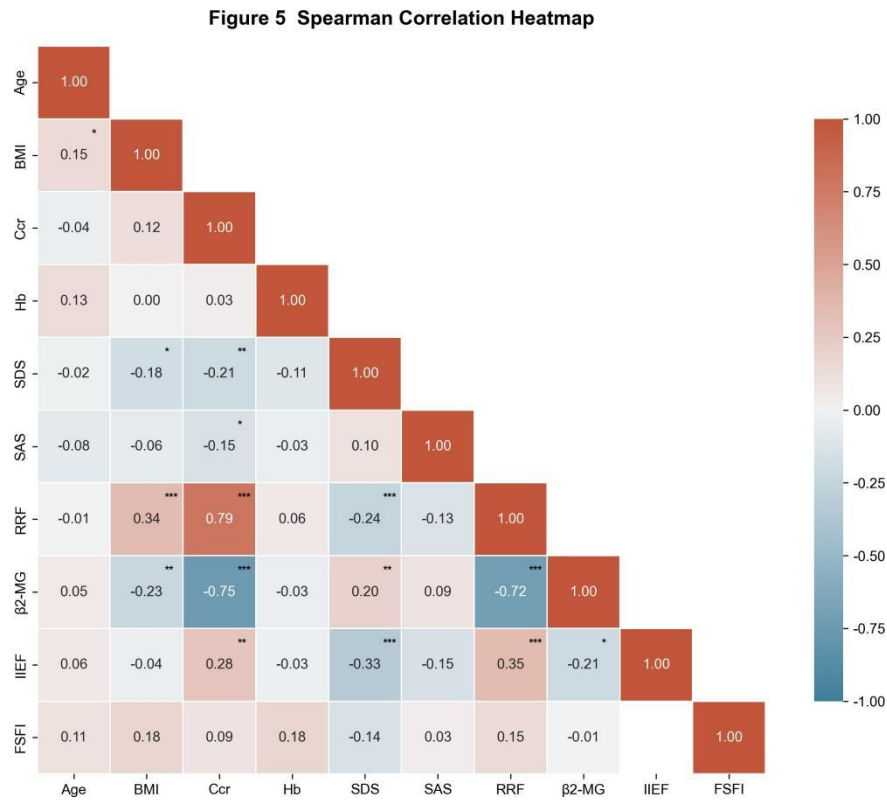


Figure 4: Spearman correlation heatmap of ten key variables. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

3.5 Multivariate Regression Analyses

3.5.1 Linear Regression

In the multivariate linear regression for male IIEF-5 ($R^2=0.505$, adjusted $R^2=0.300$, $FP = 0.0011$), marital status (married vs. unmarried: $\beta=+8.77$, $P = 0.0003$), SDS ($\beta=-0.24$, $P = 0.013$), RRF ($\beta=+0.005$, $P = 0.021$), and α -blocker use ($\beta=-4.14$, $P = 0.013$) were independently associated with IIEF-5 scores. Age showed a marginal association ($\beta=-0.17$, $P = 0.096$). For female FSFI, only marital status reached significance ($\beta=+9.76$, $P = 0.010$), with modest model fit ($R^2=0.367$).

3.5.2 Logistic Regression

Logistic regression models demonstrated good discriminative performance (Table 2). Marital

status was the strongest protective factor for overall SD (OR=0.36, 95% CI: 0.15–0.87) and female FSD (OR=0.26, 95% CI: 0.08–0.82). Beta-blocker use was a significant risk factor for overall SD (OR=2.10, 95% CI: 1.12–3.93) and male ED (OR=2.32, 95% CI: 1.05–5.14).

Table 2: Multivariate logistic regression results

Model	AUC^c	<i>n</i>	Top protective factor	Top risk factor
Overall SD	0.808	209	Married (OR=0.36)	Beta-blocker (OR=2.10)
Male ED	0.860	100	Junior education (OR=0.60)	Beta-blocker (OR=2.32)
Female FSD	0.850	109	Married (OR=0.26)	ARB (OR=1.96)

^cIn-sample AUC (model fitted and evaluated on the same dataset). Test-set AUCs from the machine learning pipeline were 0.772, 0.672, and 0.541, respectively.

VIF analysis identified albumin (VIF=55.7), BMI (VIF=51.7), and hemoglobin (VIF=40.2) as having high collinearity. L2 regularization was applied in the logistic regression implementation to mitigate the impact of multicollinearity on coefficient estimation.

3.6 Machine Learning Prediction Models

3.6.1 Overall Model Performance

Among the eight algorithms evaluated for overall SD prediction, CatBoost achieved the highest test-set AUC (0.808), followed closely by the ensemble model (AUC=0.801) (Table 3, Figure 5). However, CatBoost exhibited high specificity (1.000) but low sensitivity (0.606), suggesting a conservative classification threshold. The Random Forest model achieved the highest Youden index (0.646), indicating the best combined sensitivity and specificity. The 5-fold CV AUCs (0.53–0.62) were substantially lower than test-set AUCs, suggesting that the single random split may be optimistically biased given the small test-set size ($n \approx 42$), and that cross-validated

estimates likely reflect more realistic generalization performance.

Table 3: Performance comparison of machine learning models for overall sexual dysfunction prediction

Model	AUC	Acc	Sens	Spec	F1	Youden	CV AUC
CatBoost	0.808	0.690	0.606	1.000	0.755	0.606	0.564±0.075
Ensemble	0.801	0.738	0.697	0.889	0.807	0.586	0.562±0.062
Random Forest	0.774	0.786	0.758	0.889	0.847	0.646	0.601±0.050
Logistic Reg.	0.771	0.762	0.758	0.778	0.833	0.535	0.582±0.082
SVM	0.700	0.762	0.788	0.667	0.839	0.455	0.615±0.061
XGBoost	0.717	0.786	0.848	0.556	0.862	0.404	0.566±0.082
LightGBM	0.677	0.810	0.909	0.444	0.882	0.354	0.531±0.097
Decision Tree	0.690	0.714	0.727	0.667	0.800	0.394	0.544±0.101

Abbreviations: Acc=accuracy; Sens=sensitivity; Spec=specificity; CV=cross-validation.

Bold values indicate best performance for each metric.

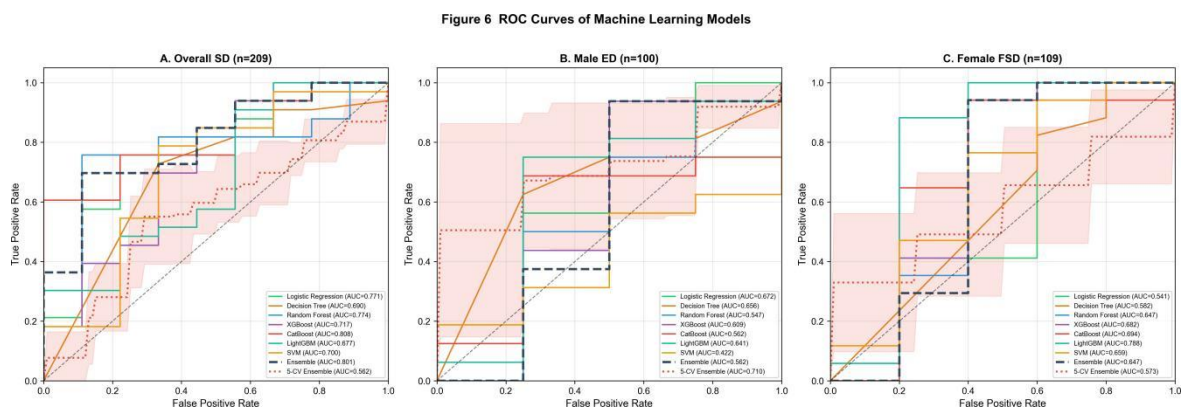


Figure 5: Receiver operating characteristic curves of machine learning models. (A) Overall SD; (B) Male ED; (C) Female FSD. Solid lines represent test-set ROC curves; dashed lines indicate the ensemble model; dotted lines show 5-fold cross-validation mean ROC with 95%

confidence bands (red shading).

3.6.2 Sex-Stratified Models

For male ED prediction, model performance was limited (highest AUC=0.672 for Logistic Re-gression), likely reflecting the small sample size ($n=100$, test set ≈ 20) and outcome imbalance (ED prevalence 78%). For female FSD, LightGBM achieved the best AUC (0.788) with balanced sensitivity (0.882) and specificity (0.800).

3.7 SHAP Explainability Analysis

SHAP analysis of the Random Forest model (selected for its interpretability and balanced performance) identified the top predictors of overall SD (Figure 6, Figure 8). Depression severity (SDS) was the dominant predictor with a mean $|\text{SHAP}|$ value of 0.0455, approximately 1.6 times higher than the second-ranked feature. Residual renal function (0.0291), β_2 -microglobulin (0.0234), and hemoglobin (0.0223) followed.

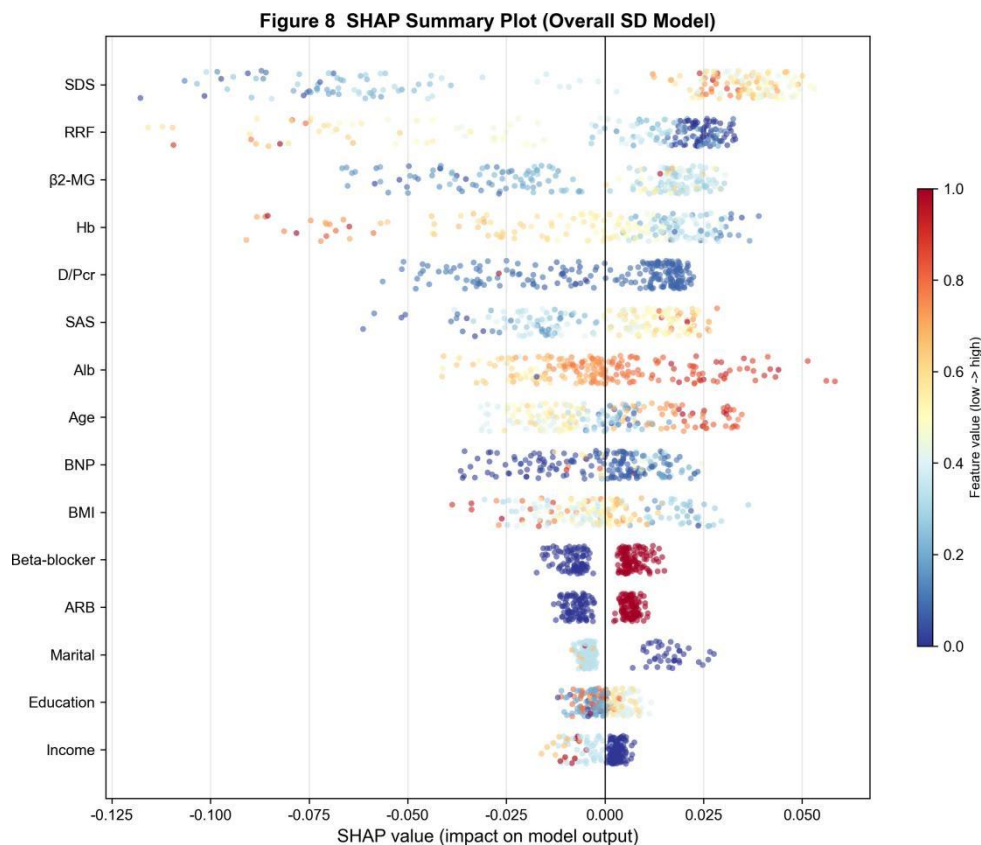


Figure 6: SHAP summary plot for the overall sexual dysfunction model. Each point is one patient. Color encodes the feature value (red = high, blue = low), and horizontal position gives the SHAP value, i.e., that feature's contribution to the prediction.

SHAP dependence plots for the top four contributing features appear in Figure 7. SDS and SD risk were almost monotonically related: as SDS increased, so did the predicted risk. RRF was the mirror image. Its protective effect concentrated at the lower end of the distribution, where the dependence curve fell sharply. Hemoglobin was similarly protective. By contrast, β 2-MG was positively associated with risk, with higher values pushing the prediction upward.

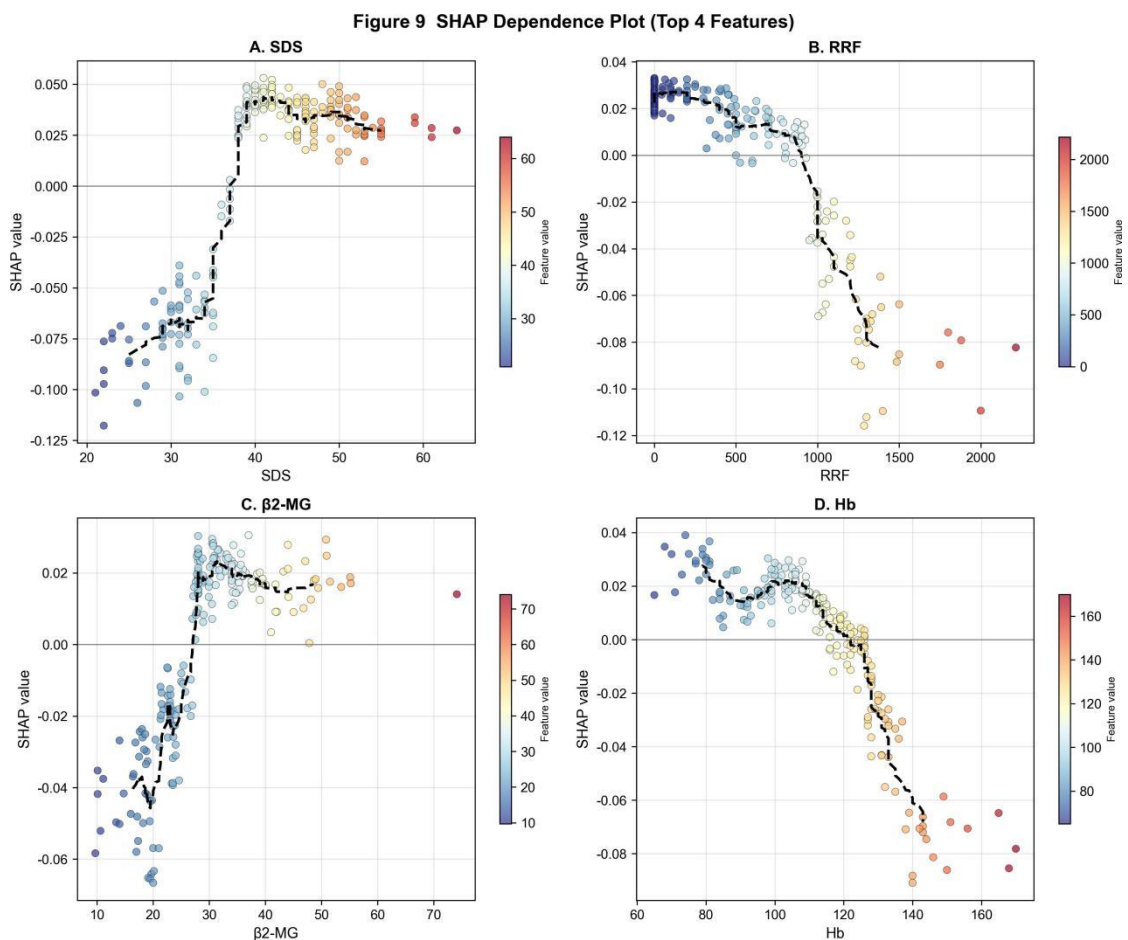


Figure 7: SHAP dependence plots for the top four predictive features. Dashed lines represent local regression smoothers. (A) SDS; (B) RRF; (C) β ₂-MG; (D) Hemoglobin.

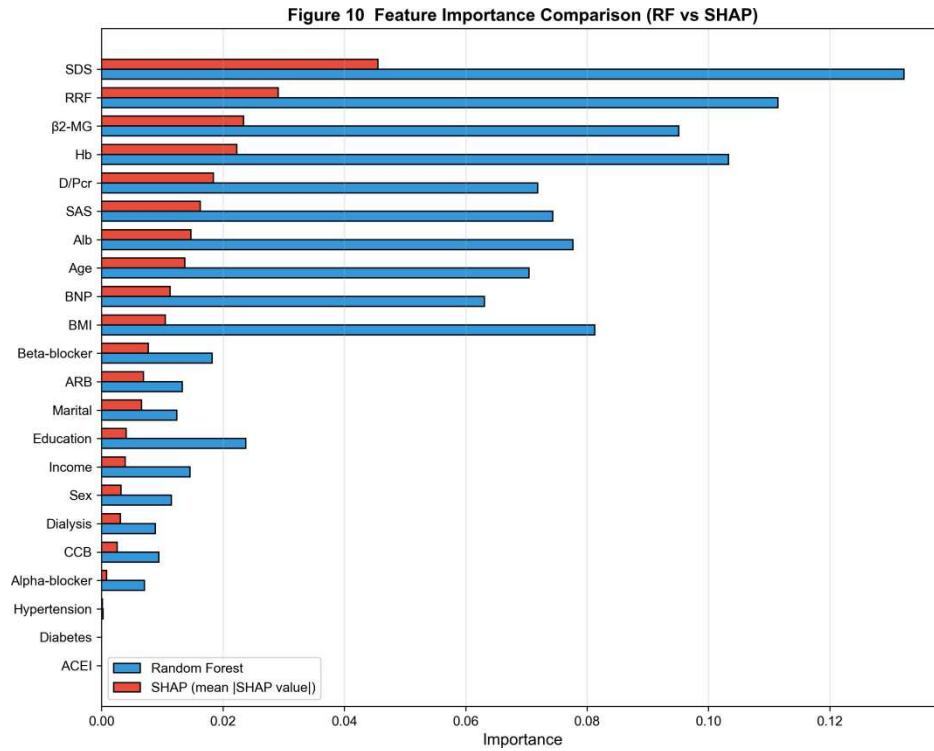


Figure 8: Comparison of feature importance rankings between Random Forest (built-in Gini importance) and SHAP (mean absolute SHAP value).

3.8 Subgroup and Sensitivity Analyses

Subgroup analyses revealed differential risk factor profiles across strata (Table 4). In males, physiological factors (Ccr, RRF, β 2-MG) were significantly associated with SD, whereas in females, hemoglobin and marital status predominated. Age-stratified analysis showed that younger patients (≤ 40 years) were more influenced by psychosocial factors (SDS, income, marital status), while older patients (> 40 years) showed stronger associations with physiological parameters (RRF, β 2-MG). In patients with depression ($\text{SDS} \geq 50$), physiological factors were no longer significantly associated with SD, Depression may exert a dominant effect that overshadows biological determinants.

Table 4: Subgroup analysis: Significant univariate associations by stratum

Subgroup	Significant variables	Predominant domain	
Male ($n=100$)	Ccr, RRF, β_2 -MG, SDS	Physiological + psychological	S
Female ($n=109$)	Hb, marital status	Anemia + social	e
Age ≤ 40 ($n=124$)	Hb, SDS, marital status, income	Psychosocial	n
Age > 40 ($n=85$)	RRF, β_2 -MG	Physiological	si
CAPD ($n=152$)	RRF, SDS, SAS	Psychological	ti
Non-CAPD ($n=57$)	Hb	Anemia	vi
No depression ($n=171$)	Ccr, RRF, β_2 -MG, income	Physiological	ty
Depression ($n=38$)	None significant	Depression-dominant	a
			n
			al

ysis: complete-case analysis (134 patients retained) improved the logistic regression AUC from 0.737 to 0.841. This shift suggests the missing data pattern itself may carry usable information. Excluding high-VIF variables (albumin and BMI) brought the AUC down to 0.744, a modest drop, pointing to reasonable robustness against multicollinearity.

4 Discussion

In this cohort of 209 PD patients, 77.5% met criteria for sexual dysfunction, with men and women affected at near-identical rates (78.0% vs. 77.1%). Depression, measured by SDS, was the dominant predictor across every analytical approach we applied. Residual renal function protected against SD; beta-blocker use roughly doubled the risk. Our machine learning models discriminated adequately, and SHAP-based explanations clarified which variables drove individual risk rather than group-level averages.

A prevalence of 77.5% is high but consistent with other dialysis cohorts¹⁵, though cross-study comparison is hampered by heterogeneity in assessment instruments and diagnostic thresholds.

Fu et al. reported ED in 56.9% of male CKD patients in China, but their cohort was less severely ill¹⁵. The near-identical sex distribution in our data challenges the usual framing of SD as a male concern and supports routine screening in both sexes. Depression overwhelmed other risk factors in our analysis: in the subgroup with SDS ≥ 50 , physiological variables that were meaningful elsewhere lost statistical significance. The underlying biology is tangled. Neuroendocrine disruption suppresses androgen production. Libido drops. Antidepressants add their own sexual side effects. Partner communication frays under chronic illness^{16,17}. None of these pathways acts alone, but the practical implication is that treating depression may be the most efficient route to improving sexual function. RRF ranked second in SHAP importance and showed a consistent protective signal. The likely mechanisms include better clearance of uremic toxins, more stable volume and blood pressure control, preserved renal endocrine function, and lower systemic inflammation^{18,19}. These effects, modest individually, appear additive, which strengthens the case for RRF-preserving dialysis strategies². Beta-blocker use was associated with a doubling of SD odds (OR = 2.10-2.32). Unopposed α -adrenergic tone, reduced testosterone, and central suppression of desire are the proposed mediators^{20,21}. For male patients with ED on beta-blockers, a regimen review is reasonable where cardiovascular status permits, though our finding that ARB use was associated with higher FSD risk in women (OR = 1.96) cautions against assuming that any alternative antihypertensive is benign²².

Our ML models did not dramatically outperform logistic regression. CatBoost reached an AUC of 0.808 on the test set; logistic regression managed 0.771. The clinical contribution came from SHAP, which decomposes predictions to the individual patient level, revealing which factors drive a given risk estimate and by how much²³. For a condition as heterogeneous as SD in PD, where two patients with similar predicted probabilities may arrive at that risk through different routes, individualized interpretation is more useful than a group-level odds ratio. A candid caveat is necessary. The five-fold cross-validation AUCs ranged

from 0.56 to 0.62, well below the test-set estimates. The single random split, evaluated on roughly 42 patients, likely produced an optimistic result. Two hundred nine patients is defensible for regression but small for machine learning given the high feature-to-sample ratio^{8,23,24}. External validation will determine whether these models capture signal or noise. Age-stratified analyses revealed a divergence worth noting: patients under 40 showed stronger associations with psychosocial variables (depression, marital status, income), while those over 40 tracked more closely with physiological parameters, notably RRF and β 2-microglobulin.

Our study has specific strengths and equally specific weaknesses. We used validated sex-specific instruments (IIEF-5 and FSFI) that capture the different ways SD manifests in men and women. We examined biochemical, psychological, pharmacological, and social risk factors within a single analysis. We applied explainable AI to a nephrology question, an approach that remains uncommon. These strengths must be weighed against the cross-sectional design, which precludes causal inference regardless of statistical adjustment. The single-center setting limits generalizability. We did not measure hormonal parameters: no testosterone, estradiol, prolactin, FSH, or LH, all directly relevant to the outcome. Dialysis adequacy was assessed coarsely. The high SD prevalence created outcome imbalance that may have affected model calibration. Missing values required imputation; although this was the best available approach, it introduces uncertainty that downstream analyses cannot fully propagate.

5 Conclusion

Sexual dysfunction affects more than three-quarters of PD patients, with comparable prevalence in males and females. Depression is the strongest modifiable risk factor, residual renal function is a key protective factor, and beta-blocker use is an important pharmacological risk factor. ML models may be useful for individualized risk prediction in this population. Future multicenter

prospective studies are needed to validate these predictive models and to evaluate the impact of targeted interventions on sexual function outcomes.

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Author Contributions

L.D.: Conceptualization, Methodology, Writing - Original Draft. D.Z.: Data Curation, Investigation. Q.C.: Formal Analysis. D.L.: Visualization. L.L.: Supervision, Writing - Review & Editing. J.L.: Project Administration, Funding Acquisition.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Ethics Committee of Xinqiao Hospital (Approval No. 2026-052-01).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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