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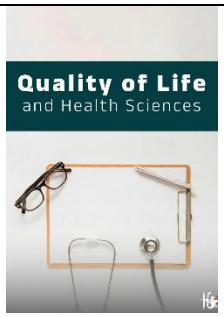

Machine Learning Prediction of Low Quality of Life in Patients With Chronic Kidney Disease Using XGBoost and Explainable Artificial Intelligence

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A B S T R A C T

Objective: This study aimed to predict low quality of life among patients with chronic kidney disease using the XGBoost machine learning algorithm and to identify the most important predictors through SHAP-based explainable artificial intelligence analysis.
Methods and Materials: This cross-sectional predictive modeling study was conducted among 426 patients with chronic kidney disease in Tehran, Iran. Data were collected using a demographic and clinical information checklist, medical record data, laboratory indicators, and the Kidney Disease Quality of Life questionnaire. Low quality of life was defined as a total quality-of-life score below 50 and was used as the binary outcome variable. After data preprocessing, missing-value management, and encoding of categorical variables, the dataset was divided into training and testing sets. Logistic regression, support vector machine, random forest, and XGBoost models were developed and compared. Five-fold cross-validation and hyperparameter tuning were applied to optimize model performance. The final model was interpreted using SHAP values to determine global and patient-level feature importance.
Findings: Patients with low quality of life had significantly longer disease duration, lower estimated glomerular filtration rate, higher dialysis frequency, longer dialysis duration, more comorbidities, greater medication burden, lower hemoglobin, lower serum albumin, higher serum phosphorus, and higher serum creatinine levels than patients without low quality of life ($p < 0.05$). Among the evaluated models, XGBoost showed the strongest predictive performance, with accuracy of 0.847, sensitivity of 0.829, specificity of 0.860, precision of 0.806, F1-score of 0.817, and area under the receiver operating characteristic curve of 0.912. SHAP analysis identified burden of kidney disease score, serum albumin, hemoglobin, estimated glomerular filtration rate, number of comorbidities, dialysis status, disease duration, serum phosphorus, cardiovascular disease, and number of prescribed medications as the most influential predictors.
Conclusion: The XGBoost model demonstrated strong and interpretable performance in predicting low quality of life among patients with chronic kidney disease, and SHAP analysis showed that patient-reported burden, renal function, anemia, nutritional status, comorbidity load, and treatment-related factors jointly contributed to risk prediction.
Keywords: *Chronic kidney disease; quality of life; machine learning; XGBoost; explainable artificial intelligence; SHAP; predictive modeling.*

1. Introduction

Chronic kidney disease is a progressive, multidimensional, and clinically burdensome condition that affects not only renal function but also cardiovascular health, metabolic stability, physical capacity, psychological well-being, social participation, and overall quality of life. As kidney function declines, patients frequently experience a growing accumulation of symptoms, treatment demands, dietary restrictions, medication burden, uncertainty about disease progression, and dependence on specialized care. Contemporary nephrology has therefore shifted from a narrow focus on biochemical control and survival toward a broader understanding of chronic kidney disease as a long-term condition requiring risk prediction, early identification of deterioration, multidisciplinary management, and patient-centered outcome assessment. Recent calls to identify and prevent chronic kidney disease emphasize that early recognition, structured screening, and coordinated intervention are essential for reducing disease progression and its broader health consequences (Ferro et al., 2025). Similarly, the gap between what is known about kidney care and what is implemented in practice remains a central challenge, particularly because many patients continue to experience delayed diagnosis, fragmented care, insufficient risk stratification, and limited integration of patient-reported outcomes into routine clinical decision-making (Luyckx et al., 2024). In this context, quality of life is not a secondary or optional outcome but a core indicator of disease impact, treatment success, and clinical priority.

The clinical burden of chronic kidney disease is intensified by its close interaction with cardiovascular, metabolic, inflammatory, hematologic, skeletal, and psychological pathways. Patients with advanced chronic kidney disease are at increased risk of cardiovascular disease, hospitalization, functional decline, and premature mortality, and their care often requires complex management decisions across nephrology, cardiology, endocrinology, nutrition, rehabilitation, and mental health domains (Shrestha et al., 2024). Cardiovascular complications are particularly important among patients receiving dialysis, as cardiac dysfunction, vascular calcification, arrhythmia risk, and hemodynamic stress contribute substantially to morbidity and mortality (Echefu et al., 2023). Broader cardiorenal metabolic conditions impose major humanistic and economic burdens by affecting physical functioning, daily activities, psychological adjustment, and healthcare utilization (Ferdinand et al., 2023). Shared-care models for cardiorenal metabolic syndrome further demonstrate that patients with overlapping kidney, cardiovascular, and metabolic disorders require integrated approaches rather than isolated disease-specific management (Lavery et al., 2022). These overlapping disease pathways make quality of life difficult to predict through single clinical indicators, because patient outcomes are shaped by multiple interacting biological and psychosocial factors.

Quality of life in chronic kidney disease is strongly influenced by disease stage, symptom burden, treatment modality, nutritional status, anemia, bone-mineral disorders, frailty, and comorbid illness. Dialysis may extend survival, yet it also introduces time-consuming treatment routines, fatigue, vascular access complications, dietary limitations, sleep disruption, social restriction, and emotional burden. In aging societies, extending the healthy life span of dialysis patients requires attention not only to longevity but also to functional independence, psychological adaptation, symptom control, and maintenance of meaningful daily life (Inaba & Mori, 2021). The complexity of advanced kidney disease also highlights the importance of multidisciplinary care teams, as coordinated clinical management may improve monitoring, treatment adjustment, and continuity of care for patients with chronic kidney disease (Abe et al., 2025). In parallel, frailty has become an increasingly important construct across medical specialties because it captures vulnerability, reduced physiological reserve, and increased susceptibility to poor outcomes; integrating frailty assessment into specialty care may improve risk identification among patients with chronic illnesses, including those with kidney disease (Singh et al., 2024). Nutrition, sarcopenia, frailty, and comorbidities are also closely related in older adults, suggesting that physical decline and nutritional compromise may directly and indirectly reduce quality of life among patients with chronic conditions (Yoshida et al., 2023).

Several laboratory and clinical variables may contribute to reduced quality of life among patients with chronic kidney disease. Anemia is one of the most clinically relevant complications because reduced hemoglobin may worsen fatigue, exercise intolerance, cognitive difficulties, depression, and reduced physical functioning. Evidence from elderly patients with acute stroke has also indicated that anemia and renal dysfunction may coexist in clinically vulnerable populations, reinforcing the importance of hematologic indicators in evaluating disease severity and functional risk (Mori et al., 2023). Platelet count and platelet volume have also been examined in patients with chronic

kidney disease, reflecting growing interest in hematologic markers that may provide information about inflammation, vascular risk, and disease status (Davis et al., 2023). Iron deficiency has been shown to affect diastolic function, aerobic exercise capacity, and patient phenotyping in heart failure with preserved ejection fraction, which is relevant to chronic kidney disease because anemia, iron dysregulation, cardiovascular dysfunction, and reduced exercise capacity frequently overlap in cardiorenal populations (Gevaert et al., 2022). These findings support the inclusion of laboratory indicators such as hemoglobin, albumin, phosphorus, creatinine, and other biochemical markers in predictive models of patient-reported outcomes.

Mineral and bone disorders are another major source of disease burden in chronic kidney disease. Abnormalities in calcium, phosphorus, parathyroid hormone, vitamin D metabolism, fibroblast growth factor 23, and bone turnover may contribute to pain, fractures, vascular calcification, reduced mobility, and decreased functional capacity. Evaluating osteoporosis in chronic kidney disease requires attention to both bone quantity and bone quality, because conventional measures may not fully capture skeletal fragility in this population (Lloret et al., 2024). The role of fibroblast growth factor 23 remains debated as a direct contributor, biomarker, or both, but its importance in chronic kidney disease illustrates the broader difficulty of distinguishing between markers of risk and mechanisms of harm (Komaba & Fukagawa, 2021). Klotho has also been investigated as a biomarker related to aging, cardiovascular risk, and mortality in women with acute coronary syndrome, and although this evidence is not limited to nephrology, it is relevant to the biological overlap between kidney function, vascular aging, and systemic decline (Cortés et al., 2025). The gut-kidney and oral-kidney axes have further expanded the understanding of chronic kidney disease pathophysiology, with gut dysbiosis and oral disease proposed as contributors to inflammation, uremic toxin accumulation, immune dysregulation, and systemic complications (Altamura et al., 2023). These mechanisms suggest that low quality of life in chronic kidney disease may be driven by multiple interconnected pathways rather than by kidney filtration alone.

Psychological symptoms are also central to quality of life in kidney disease. Depression, anxiety, illness-related distress, fear of disease progression, reduced perceived control, and uncertainty about treatment may worsen symptom perception and decrease adherence to self-management behaviors. Among adults with diabetic kidney disease, depression and anxiety have been associated with quality of life, indicating that psychological distress is an important dimension of kidney-related burden and should be considered when evaluating patient outcomes (Shen et al., 2022). In other complex clinical populations, kidney failure and psychological distress have also been examined as predictors of treatment toxicity and quality of life, further emphasizing that renal dysfunction and mental health may jointly shape clinical vulnerability and patient-reported outcomes (Jicman et al., 2025). Lifestyle factors represent another modifiable domain, as bibliometric evidence on chronic kidney disease and lifestyle emphasizes the relevance of physical activity, diet, smoking, obesity, and other behavioral factors in prevention and disease management (Yin et al., 2022). Screening and care optimization in resource-limited settings also matter, as work on diabetic retinopathy screening among uninsured Latinx patients demonstrates the need for efficient, equity-oriented clinical systems that identify high-risk individuals and allocate limited resources effectively (Bu et al., 2024). For chronic kidney disease, similar principles apply: prediction models may help clinicians identify patients most likely to experience low quality of life and prioritize supportive interventions.

Traditional statistical approaches have contributed substantially to understanding chronic kidney disease outcomes, yet they may be limited when the outcome is shaped by nonlinear relationships, high-dimensional predictors, interaction effects, and heterogeneous patient profiles. Risk prediction in nondialysis chronic kidney disease has been a continuing challenge, especially for cardiovascular disease outcomes, where model performance may depend on the availability of clinical, demographic, laboratory, imaging, and comorbidity data (Streja et al., 2021). The Kidney Failure Risk Equation and classification systems such as the Oxford Classification in IgA nephropathy reflect the broader movement toward structured prognostic estimation in nephrology, demonstrating that risk models can support individualized prediction and clinical decision-making (Toal et al., 2025). Clinical trial design in chronic kidney disease has also increasingly relied on careful characterization of disease progression, inclusion criteria, biochemical profiles, and outcome trajectories, as illustrated by the VALOR-CKD study evaluating veverimer in patients with metabolic acidosis (Mathur et al., 2022). Modeling studies in chronic kidney disease among patients with type 2 diabetes further show that predictive tools depend heavily on data sources, derivation cohorts, assumptions, and model

structure (Pöhlmann et al., 2022). These developments suggest that machine learning may offer additional value by handling complex predictor patterns that are difficult to capture with conventional regression-based models.

Machine learning approaches are increasingly used in medicine to improve risk stratification, pattern recognition, and individualized prediction. In chronic kidney disease, machine learning has potential utility because relevant predictors may include demographic characteristics, comorbidities, symptoms, medication burden, dialysis status, laboratory values, and patient-reported measures, all of which may interact in nonlinear ways. Radiomics and elastography ultrasound have been used to predict progression of kidney injury, demonstrating the growing use of advanced computational signatures in nephrology-related prediction (Zhu et al., 2022). Beyond nephrology, prognostic modeling based on biological markers has been used in oncology and hematology, such as the assessment of tumor-associated neutrophils in breast cancer and the role of minimal residual disease in indolent non-Hodgkin lymphoma, illustrating the broader movement toward precision medicine and individualized risk interpretation across clinical disciplines (Giudice et al., 2021; Kakumoto, 2024). Glomerular hyperfiltration has also been discussed as a clinically significant phenomenon in children, showing that kidney-related risk may begin before overt renal decline and that early physiological markers can have long-term clinical significance (Adebayo et al., 2022). These examples support the value of predictive frameworks that can incorporate heterogeneous markers and produce clinically meaningful estimates of risk.

Among machine learning algorithms, Extreme Gradient Boosting, known as XGBoost, is particularly suitable for structured clinical datasets because it can model nonlinear associations, manage interactions among predictors, handle mixed variable types, and often achieve high predictive performance in tabular health data. However, high-performing prediction alone is not sufficient in clinical medicine. For a model to be clinically acceptable, it must be interpretable, transparent, and able to indicate why a patient is classified as high risk. Explainable artificial intelligence methods, especially SHAP-based feature importance analysis, can address this limitation by estimating the contribution of each predictor to model output at both global and individual levels. In chronic kidney disease, this is especially important because clinicians need to know whether predictions are driven by disease severity, dialysis status, comorbidity load, anemia, nutritional markers, biochemical imbalance, psychological distress, or patient-reported burden. Explainability therefore allows machine learning models to move beyond black-box classification and become tools for clinical reasoning, risk communication, and targeted intervention planning.

Despite increasing interest in prognostic modeling in nephrology, limited research has focused specifically on predicting low quality of life among patients with chronic kidney disease using an explainable machine learning framework. Much of the existing literature emphasizes kidney failure progression, cardiovascular risk, biochemical outcomes, mortality, or treatment response, while patient-reported quality of life remains less frequently modeled as a primary predictive target. This represents an important gap because low quality of life may indicate unmet clinical needs, psychosocial distress, treatment intolerance, poor functional status, and increased vulnerability before severe medical deterioration becomes apparent. A machine learning model that predicts low quality of life and explains the relative contribution of demographic, clinical, laboratory, and treatment-related factors may support earlier identification of high-risk patients and facilitate more patient-centered care planning. Therefore, the aim of this study was to predict low quality of life among patients with chronic kidney disease using the XGBoost machine learning algorithm and to interpret the most important predictors through SHAP-based explainable artificial intelligence analysis.

2. Methods and Materials

2.1. Study Design and Participants

This study was conducted as a cross-sectional predictive modeling study among patients with chronic kidney disease in Tehran, Iran. The primary objective was to develop and explain a machine learning model for predicting low health-related quality of life in patients with chronic kidney disease using the XGBoost algorithm and explainable artificial intelligence methods. The study population consisted of adult patients with a confirmed diagnosis of chronic kidney disease who were receiving outpatient nephrology care or dialysis-related follow-up services in selected nephrology clinics, dialysis centers, and hospital-affiliated kidney disease units in Tehran. Participants were recruited through convenience sampling based on eligibility criteria and willingness to participate in the study. The final sample included 426 patients with chronic kidney disease. Inclusion criteria were age 18 years or older, confirmed diagnosis of

chronic kidney disease for at least six months, availability of relevant clinical and laboratory information in the medical record, ability to understand and complete the study questionnaires, and provision of informed consent. Patients were excluded if they had severe cognitive impairment, active psychosis, acute medical instability at the time of data collection, recent hospitalization due to a life-threatening complication, incomplete questionnaire data, or missing key clinical variables required for machine learning analysis. Before data collection, the purpose of the study was explained to all participants, and they were assured that participation was voluntary, that their information would remain confidential, and that withdrawal from the study would not affect their treatment or clinical care.

2.2. Measures

Data were collected using a demographic and clinical information checklist, the Kidney Disease Quality of Life questionnaire, and information extracted from patients' medical records. The demographic and clinical information checklist was designed to collect variables that may be associated with quality of life in patients with chronic kidney disease. Demographic variables included age, sex, marital status, educational level, employment status, monthly income level, living status, smoking status, and body mass index. Clinical variables included duration of chronic kidney disease, stage of kidney disease, estimated glomerular filtration rate, dialysis status, duration of dialysis among patients receiving dialysis, type of treatment, history of kidney transplantation, presence of diabetes mellitus, hypertension, cardiovascular disease, anemia, and other comorbid conditions. Laboratory and treatment-related variables were extracted from the most recent available medical records and included serum creatinine, blood urea nitrogen, hemoglobin, serum albumin, calcium, phosphorus, potassium, parathyroid hormone level when available, and number of prescribed medications. These variables were selected because they represent demographic, clinical, biochemical, and treatment-related characteristics that may contribute to impaired quality of life in patients with chronic kidney disease.

Health-related quality of life was assessed using the Kidney Disease Quality of Life 36-item questionnaire. This instrument is widely used for measuring quality of life among patients with chronic kidney disease and includes both generic and kidney disease-specific dimensions. The questionnaire contains items related to physical functioning, mental health, burden of kidney disease, symptoms and problems of kidney disease, and effects of kidney disease on daily life. Scores are transformed to a scale ranging from 0 to 100, with higher scores indicating better perceived quality of life. In the present study, the overall quality-of-life score was calculated according to the standard scoring procedure, and low quality of life was defined as a total quality-of-life score below 50. Based on this cut-off point, participants were classified into two groups: patients with low quality of life and patients without low quality of life. This binary classification was used as the target outcome variable for machine learning prediction. The Persian version of the questionnaire was used, and previous studies have confirmed the validity and reliability of this instrument among Iranian patients with chronic diseases and kidney-related conditions.

2.3. Data Analysis

Data analysis was performed in two main stages: conventional descriptive analysis and machine learning prediction. First, the dataset was checked for completeness, accuracy, outliers, and missing values. Missing values were examined for each variable, and variables with excessive missingness were excluded from the modeling process. For variables with acceptable levels of missing data, numerical variables were imputed using median values, and categorical variables were imputed using the most frequent category. Continuous variables were described using mean and standard deviation or median and interquartile range depending on the distribution of the data, while categorical variables were described using frequency and percentage. Before model development, all predictor variables were reviewed for clinical relevance and data quality. Categorical variables were encoded into numerical format, and continuous variables were retained in their original scale because tree-based algorithms such as XGBoost do not require strict normalization. The target variable was low quality of life, defined as a binary outcome based on the quality-of-life score.

The predictive model was developed using Extreme Gradient Boosting, known as XGBoost, because this algorithm is highly suitable for structured clinical datasets and can model complex nonlinear associations and interactions among demographic, clinical, laboratory, and treatment-related variables. The dataset was randomly divided into training and testing sets, with 80% of the data used for model training and 20% reserved for final model

evaluation. To improve the robustness of the model and reduce the risk of overfitting, five-fold cross-validation was applied within the training set. Hyperparameters, including learning rate, maximum tree depth, number of estimators, subsampling ratio, column sampling ratio, and regularization parameters, were optimized through grid search based on cross-validation performance. Because low quality of life may not be equally distributed across outcome classes, class imbalance was assessed before modeling. When imbalance was detected, class weighting was applied during model training to improve sensitivity for the low-quality-of-life group. Model performance was evaluated using accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve. The area under the curve was considered the main discrimination index because it reflects the model's ability to distinguish between patients with and without low quality of life across different classification thresholds.

Explainable artificial intelligence analysis was performed using SHAP values to interpret the final XGBoost model. SHAP analysis was used to identify the most influential predictors of low quality of life and to explain the direction and magnitude of each variable's contribution to the model output. Global feature importance was examined to determine which demographic, clinical, laboratory, and treatment-related variables had the strongest overall impact on prediction. In addition, local explanations were generated to show how specific patient-level characteristics increased or decreased the predicted probability of low quality of life for individual cases. This approach allowed the predictive model to be interpreted not only in terms of statistical performance but also in terms of clinical meaning. The integration of XGBoost with SHAP-based explainability provided a transparent framework for identifying high-risk patients and clarifying the factors most strongly associated with low quality of life among patients with chronic kidney disease.

3. Findings and Results

A total of 426 patients with chronic kidney disease from Tehran were included in the final analysis. The mean age of the participants was 57.84 ± 13.62 years, and the sample included 241 men (56.6%) and 185 women (43.4%). Most participants were married (n = 306, 71.8%), while 120 participants (28.2%) were single, divorced, or widowed. Regarding educational status, 141 participants (33.1%) had below-diploma education, 160 participants (37.6%) had a diploma, and 125 participants (29.3%) had university education. In terms of employment status, 139 participants (32.6%) were employed, 112 participants (26.3%) were retired, 116 participants (27.2%) were unemployed, and 59 participants (13.8%) were homemakers. Based on the predefined cut-off point for the quality-of-life score, 178 patients (41.8%) were classified as having low quality of life, while 248 patients (58.2%) were classified as not having low quality of life. The dataset was therefore appropriate for binary classification modeling, with a clinically meaningful proportion of patients belonging to the low-quality-of-life group.

Table 1

Clinical, laboratory, and quality-of-life characteristics of patients according to quality-of-life status

Variable	Total sample (N = 426)	Non-low quality of life (n = 248)	Low quality of life (n = 178)	p-value
Duration of chronic kidney disease, years, mean ± SD	6.82 ± 4.21	5.43 ± 3.64	8.75 ± 4.32	<0.001
Estimated glomerular filtration rate, mL/min/1.73 m², mean ± SD	32.61 ± 18.42	38.10 ± 18.73	24.97 ± 15.31	<0.001
Receiving dialysis, n (%)	166 (39.0)	78 (31.5)	88 (49.4)	<0.001
Duration of dialysis among dialysis patients, months, mean ± SD	42.31 ± 28.64	34.86 ± 22.41	48.92 ± 31.73	0.002
Diabetes mellitus, n (%)	186 (43.7)	95 (38.3)	91 (51.1)	0.009
Hypertension, n (%)	299 (70.2)	164 (66.1)	135 (75.8)	0.031
Cardiovascular disease, n (%)	112 (26.3)	50 (20.2)	62 (34.8)	0.001
Number of comorbidities, mean ± SD	2.08 ± 1.17	1.72 ± 1.04	2.59 ± 1.18	<0.001
Number of prescribed medications, mean ± SD	6.39 ± 2.81	5.79 ± 2.46	7.23 ± 3.04	<0.001
Hemoglobin, g/dL, mean ± SD	10.84 ± 1.69	11.31 ± 1.53	10.18 ± 1.68	<0.001
Serum albumin, g/dL, mean ± SD	3.79 ± 0.53	3.99 ± 0.42	3.51 ± 0.55	<0.001
Serum phosphorus, mg/dL, mean ± SD	4.79 ± 1.22	4.48 ± 1.07	5.22 ± 1.31	<0.001
Serum creatinine, mg/dL, mean ± SD	3.47 ± 2.11	2.94 ± 1.82	4.21 ± 2.28	<0.001
KDQOL total score, mean ± SD	56.91 ± 17.18	68.39 ± 10.52	40.93 ± 6.74	<0.001

Burden of kidney disease score, mean ± SD	50.58 ± 24.09	62.90 ± 20.31	33.42 ± 18.55	<0.001
Symptoms and problems score, mean ± SD	67.21 ± 18.76	74.41 ± 15.62	57.18 ± 18.42	<0.001
Effects of kidney disease score, mean ± SD	60.34 ± 21.39	70.22 ± 17.94	46.58 ± 18.62	<0.001

As shown in Table 1, patients classified in the low-quality-of-life group demonstrated a more severe clinical and functional profile than those without low quality of life. The low-quality-of-life group had a significantly longer duration of chronic kidney disease, lower estimated glomerular filtration rate, higher frequency of dialysis treatment, and longer dialysis duration. Comorbid conditions were also more frequent in this group, particularly diabetes mellitus, hypertension, and cardiovascular disease. Laboratory indicators further showed that patients with low quality of life had significantly lower hemoglobin and serum albumin levels and significantly higher serum phosphorus and creatinine levels, suggesting a greater burden of disease severity, metabolic disturbance, and functional impairment. In addition, the low-quality-of-life group had a higher mean number of comorbidities and prescribed medications, indicating greater clinical complexity. The quality-of-life dimensions showed large and statistically significant differences between groups. Patients with low quality of life had markedly lower total KDQOL scores as well as lower scores in burden of kidney disease, symptoms and problems, and effects of kidney disease. These findings indicate that low quality of life among patients with chronic kidney disease was not an isolated subjective outcome but was strongly associated with disease severity, treatment burden, comorbidity load, and poorer laboratory status.

Table 2

Performance comparison of machine learning models for predicting low quality of life

Model	Accuracy	Sensitivity	Specificity	Precision	F1-score	AUC
Logistic regression	0.765	0.714	0.800	0.735	0.724	0.821
Support vector machine	0.788	0.743	0.820	0.765	0.754	0.846
Random forest	0.824	0.800	0.840	0.800	0.800	0.881
XGBoost	0.847	0.829	0.860	0.806	0.817	0.912

Table 2 presents the predictive performance of the evaluated machine learning models on the independent test set. Among all models, XGBoost showed the strongest overall performance, achieving an accuracy of 0.847 and an AUC of 0.912. This result indicates that the XGBoost model had excellent discriminative ability in distinguishing patients with low quality of life from those without low quality of life. Compared with logistic regression and support vector machine models, XGBoost demonstrated higher sensitivity and specificity, suggesting better balance in identifying both high-risk and lower-risk patients. The random forest model also performed well, with an AUC of 0.881; however, its performance was still lower than that of XGBoost across most evaluation indices. The sensitivity of the XGBoost model was 0.829, indicating that approximately 82.9% of patients with low quality of life were correctly identified. Its specificity was 0.860, showing that 86.0% of patients without low quality of life were correctly classified. The F1-score of 0.817 further confirmed that the final model had a favorable balance between precision and recall. Therefore, XGBoost was selected as the final predictive model for subsequent explainable artificial intelligence analysis.

Table 3

Confusion matrix and final classification indices of the optimized XGBoost model

Classification result	Predicted non-low quality of life	Predicted low quality of life	Total
Actual non-low quality of life	43	7	50
Actual low quality of life	6	29	35
Total	49	36	85

Final XGBoost index	Value
Accuracy	0.847
Sensitivity	0.829

Specificity	0.860
Positive predictive value	0.806
Negative predictive value	0.878
F1-score	0.817
Area under the ROC curve	0.912

As reported in Table 3, the optimized XGBoost model correctly classified 72 of the 85 patients in the test set. Among 35 patients who actually had low quality of life, 29 were correctly identified as low-quality-of-life cases, while 6 were misclassified as not having low quality of life. Among 50 patients who did not have low quality of life, 43 were correctly identified, while 7 were incorrectly classified as having low quality of life. This pattern demonstrates that the model had strong ability to identify patients at risk while maintaining a low rate of false-positive classification. The negative predictive value of 0.878 indicates that when the model predicted that a patient did not have low quality of life, this prediction was highly reliable. The positive predictive value of 0.806 also indicates acceptable confidence in identifying high-risk patients. From a clinical perspective, the relatively high sensitivity is particularly important because the primary purpose of the model was to detect patients with low quality of life who may require further clinical, psychological, or social support. Overall, the confusion matrix and classification indices confirm that the final XGBoost model provided a reliable and clinically useful prediction of low quality of life among patients with chronic kidney disease.

Table 4

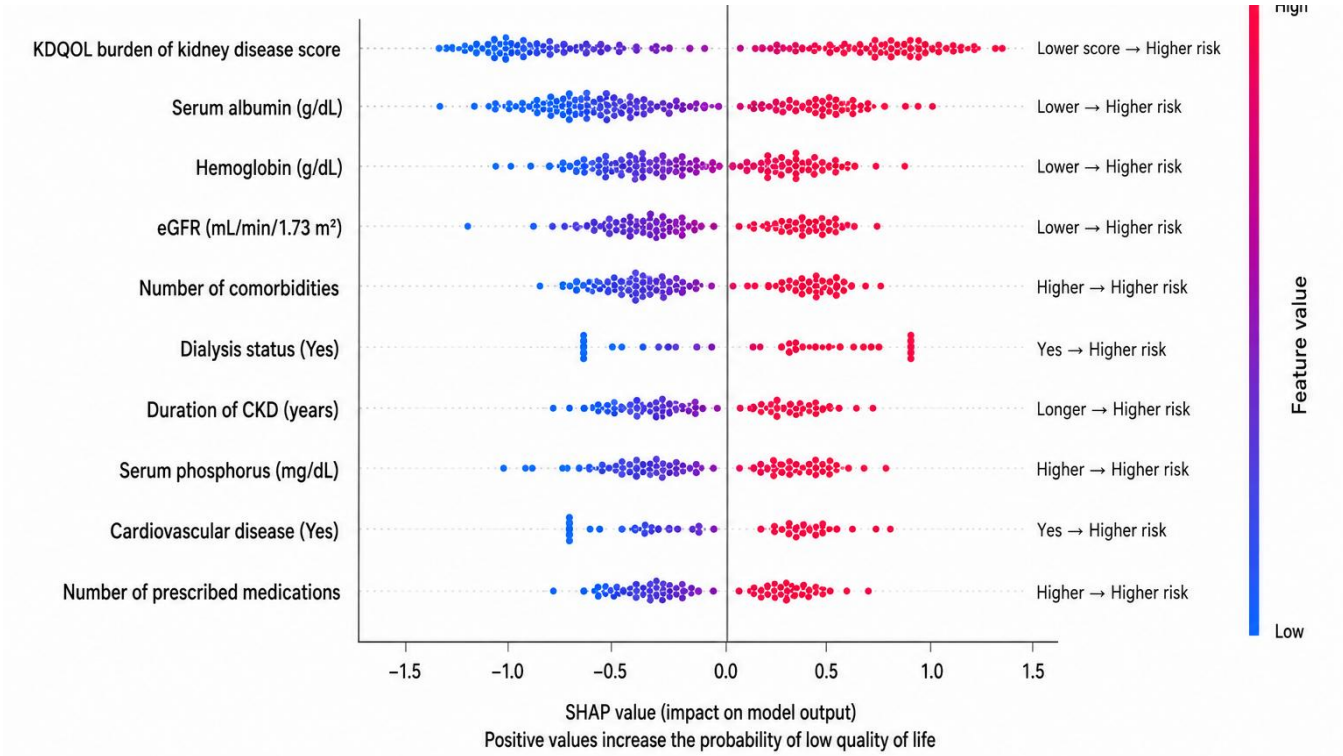
SHAP-based feature importance for predicting low quality of life using the final XGBoost model

Rank	Predictor variable	Mean absolute SHAP value	Direction of association with low quality of life
1	KDQOL burden of kidney disease score	0.284	Lower scores increased predicted risk
2	Serum albumin	0.231	Lower albumin increased predicted risk
3	Hemoglobin	0.205	Lower hemoglobin increased predicted risk
4	Estimated glomerular filtration rate	0.188	Lower eGFR increased predicted risk
5	Number of comorbidities	0.174	Higher number increased predicted risk
6	Dialysis status	0.162	Receiving dialysis increased predicted risk
7	Duration of chronic kidney disease	0.151	Longer duration increased predicted risk
8	Serum phosphorus	0.139	Higher phosphorus increased predicted risk
9	Cardiovascular disease	0.126	Presence increased predicted risk
10	Number of prescribed medications	0.113	Higher number increased predicted risk

Table 4 shows the most influential predictors in the final XGBoost model based on SHAP values. The burden of kidney disease score was the strongest predictor of low quality of life, indicating that patients who perceived kidney disease as more disruptive and burdensome had substantially higher predicted risk of low quality of life. Serum albumin and hemoglobin were the next most important predictors, showing that nutritional status and anemia-related physiological burden had major roles in the model's prediction. Lower estimated glomerular filtration rate also increased the predicted probability of low quality of life, confirming that more advanced kidney dysfunction was strongly associated with poorer patient-reported outcomes. The number of comorbidities, dialysis status, duration of chronic kidney disease, and serum phosphorus were also among the most important features, reflecting the combined effect of chronic disease progression, treatment burden, metabolic imbalance, and multimorbidity. Cardiovascular disease and number of prescribed medications contributed additional predictive information, suggesting that low quality of life was influenced not only by kidney-specific indicators but also by broader clinical complexity. The SHAP results indicate that the XGBoost model did not rely on a single dominant variable; rather, it integrated patient-reported burden, laboratory markers, kidney function, comorbidity profile, and treatment-related indicators to estimate the probability of low quality of life.

Figure 1

SHAP summary plot of the final XGBoost model for predicting low quality of life in patients with chronic kidney disease



The SHAP summary plot demonstrated the overall direction, distribution, and relative contribution of the predictors included in the final XGBoost model. The plot showed that lower burden of kidney disease scores, lower serum albumin, lower hemoglobin, lower estimated glomerular filtration rate, greater number of comorbidities, dialysis treatment, longer disease duration, higher serum phosphorus, presence of cardiovascular disease, and higher number of prescribed medications were associated with higher SHAP values and therefore increased predicted probability of low quality of life. In contrast, higher albumin, higher hemoglobin, better kidney function, fewer comorbidities, absence of dialysis, and lower perceived disease burden shifted predictions toward the non-low-quality-of-life group. This pattern confirms that the model's predictions were clinically interpretable and aligned with the expected multidimensional nature of quality of life in chronic kidney disease. The explainable artificial intelligence analysis therefore provided both predictive accuracy and interpretability, allowing the final model to identify high-risk patients while also clarifying the clinical and psychosocial factors that contributed most strongly to each prediction.

4. Discussion

The present study aimed to predict low quality of life among patients with chronic kidney disease using the XGBoost machine learning algorithm and to explain the most influential predictors through SHAP-based explainable artificial intelligence analysis. The findings showed that 41.8% of the patients were classified as having low quality of life, indicating that impaired quality of life was a frequent and clinically important condition in this sample. Patients with low quality of life had a more severe clinical profile, including longer duration of chronic kidney disease, lower estimated glomerular filtration rate, higher frequency of dialysis, longer dialysis duration, higher comorbidity burden, greater number of prescribed medications, lower hemoglobin, lower serum albumin, higher serum phosphorus, and higher serum creatinine. These findings confirm that low quality of life in chronic kidney disease is not merely a subjective or psychological complaint but reflects a multidimensional burden involving disease progression, metabolic instability, treatment dependency, cardiovascular and metabolic comorbidities, anemia, nutritional compromise, and functional vulnerability. This interpretation is consistent with the contemporary view that chronic kidney disease should be understood as a systemic and progressive condition requiring early identification, preventive care, and integrated management rather than isolated monitoring of renal function alone (Ferro et al., 2025; Luyckx et al., 2024). The observed association between advanced disease characteristics and lower quality of life is also aligned with evidence emphasizing the complex care needs of adults with advanced chronic kidney

disease, for whom symptom burden, treatment decisions, comorbidity management, and patient-centered outcomes are central components of care (Shrestha et al., 2024).

The clinical differences between patients with and without low quality of life indicate that disease severity and treatment burden are among the strongest determinants of patient-reported well-being. In the present findings, lower eGFR, dialysis treatment, and longer disease duration were clearly associated with low quality of life. These results are consistent with evidence showing that dialysis patients face unique challenges related to survival, functional decline, treatment intensity, and healthy life span, especially in aging populations (Inaba & Mori, 2021). The need for multidisciplinary care is also supported by the finding that patients with low quality of life had more comorbidities and higher medication burden, suggesting that nephrological care alone may be insufficient for improving patient outcomes (Abe et al., 2025). This is particularly relevant because chronic kidney disease commonly overlaps with cardiovascular and metabolic disorders, creating a cumulative burden that affects daily functioning, physical capacity, symptom perception, and psychological resilience. The higher prevalence of cardiovascular disease in the low-quality-of-life group supports previous discussions of the cardiorenal continuum and the high morbidity experienced by dialysis patients with cardiovascular complications (Echefu et al., 2023). Similarly, the broader humanistic and economic burden of cardiorenal metabolic conditions has been emphasized in previous systematic evidence, reinforcing the interpretation that reduced quality of life reflects the combined effect of clinical complications, care demands, and reduced functional independence (Ferdinand et al., 2023; Lavery et al., 2022).

The laboratory findings further clarify the physiological pathways through which chronic kidney disease may reduce quality of life. In this study, lower hemoglobin and lower serum albumin were strongly associated with low quality of life and were among the most influential predictors in the SHAP analysis. Low hemoglobin may contribute to fatigue, weakness, reduced exercise tolerance, cognitive difficulties, and emotional distress, all of which can directly reduce perceived quality of life. The importance of anemia is supported by evidence showing that anemia and renal dysfunction frequently coexist in vulnerable clinical populations and may signal greater systemic burden (Mori et al., 2023). Related hematologic markers, including platelet count and platelet volume, have also been examined in patients with chronic kidney disease, highlighting the broader relevance of blood-based indicators for understanding inflammation, vascular risk, and disease status (Davis et al., 2023). Low serum albumin, which emerged as one of the strongest SHAP predictors, may reflect malnutrition, inflammation, catabolic status, and frailty. This finding corresponds with evidence that nutrition, sarcopenia, frailty, and comorbidities are strongly interrelated in aging societies and may influence functional outcomes (Yoshida et al., 2023). Moreover, the broader integration of frailty into medical specialties supports the interpretation that patients with chronic kidney disease and low quality of life may represent a clinically vulnerable subgroup with reduced physiological reserve (Singh et al., 2024).

The finding that serum phosphorus and kidney-related biochemical indicators contributed to prediction is also clinically meaningful. Higher phosphorus and higher creatinine were associated with low quality of life, suggesting that metabolic dysregulation and more advanced renal impairment contribute to patient burden. Mineral and bone disorders in chronic kidney disease may reduce quality of life through pain, fracture risk, vascular calcification, physical limitation, and reduced mobility. This is consistent with evidence that both bone quantity and bone quality are important in evaluating osteoporosis in chronic kidney disease (Lloret et al., 2024). The relevance of mineral metabolism is also reflected in debates concerning fibroblast growth factor 23, which may serve as a biomarker, contributor, or both in kidney-related pathology (Komaba & Fukagawa, 2021). Furthermore, emerging biomarkers such as Klotho have been examined in relation to mortality and cardiovascular vulnerability, reinforcing the biological connection among kidney disease, vascular aging, and systemic decline (Cortés et al., 2025). The role of gut dysbiosis and oral disease in chronic kidney disease pathophysiology further supports the view that quality of life may be affected by inflammatory and systemic mechanisms beyond glomerular filtration alone (Altamura et al., 2023). Therefore, the SHAP-based ranking of laboratory and clinical markers reflects a biologically plausible model structure.

The predictive modeling results showed that XGBoost outperformed logistic regression, support vector machine, and random forest models. The optimized XGBoost model achieved an accuracy of 0.847, sensitivity of 0.829, specificity of 0.860, F1-score of 0.817, and AUC of 0.912, indicating excellent discrimination between patients with and without low quality of life. This result supports the use

of gradient boosting models for structured clinical datasets in which outcomes are shaped by nonlinear effects and interactions among demographic, clinical, laboratory, and treatment-related variables. Previous work on cardiovascular risk prediction in nondialysis chronic kidney disease has emphasized the difficulty of developing accurate models for complex renal populations and the need for improved risk stratification tools (Streja et al., 2021). Similarly, modeling studies in chronic kidney disease among patients with type 2 diabetes have shown that prediction depends heavily on data sources, derivation cohorts, model assumptions, and the way clinical trajectories are represented (Pöhlmann et al., 2022). The strong performance of XGBoost in the present study is also consistent with the broader movement toward structured prognostic estimation in nephrology, including the use of equations and classification systems for kidney failure risk and IgA nephropathy prognosis (Toal et al., 2025). Trial designs such as VALOR-CKD further show the importance of carefully defined clinical variables and progression-related outcomes in chronic kidney disease research (Mathur et al., 2022). Together, these studies support the interpretation that machine learning can add value when used to integrate multiple predictors into clinically meaningful risk estimates.

The SHAP analysis was particularly important because it showed that the final XGBoost model was not merely accurate but also interpretable. The most influential predictor was the burden of kidney disease score, followed by serum albumin, hemoglobin, eGFR, number of comorbidities, dialysis status, duration of chronic kidney disease, serum phosphorus, cardiovascular disease, and number of prescribed medications. This pattern indicates that the model combined patient-reported burden with objective biological and clinical indicators. The central role of the burden of kidney disease score is consistent with studies showing that quality of life is closely linked to psychological distress, anxiety, depression, and perceived illness burden in kidney-related populations (Shen et al., 2022). Evidence from other medically complex populations has also shown that kidney failure and psychological distress can jointly influence treatment toxicity and quality of life, supporting the interpretation that subjective distress and renal dysfunction should be examined together rather than separately (Jicman et al., 2025). The contribution of lifestyle and modifiable factors to chronic kidney disease further suggests that quality of life may be influenced by behavioral and environmental dimensions, including physical activity, diet, smoking, and self-management capacity (Yin et al., 2022). The need for efficient screening systems in resource-limited care settings also aligns with the purpose of this model, because prediction tools can help identify high-risk patients and allocate supportive resources more effectively (Bu et al., 2024).

The findings also contribute to the expanding use of advanced computational methods in nephrology and related fields. Predicting kidney injury progression using elastography ultrasound and radiomics signatures demonstrates that complex data patterns may improve risk estimation beyond conventional variables (Zhu et al., 2022). Similarly, the clinical significance of glomerular hyperfiltration in children suggests that early physiological deviations may carry prognostic meaning before overt deterioration occurs (Adebayo et al., 2022). The broader movement toward precision medicine is also evident outside nephrology, including the prognostic evaluation of tumor-associated neutrophils in breast cancer and the role of minimal residual disease in indolent non-Hodgkin lymphoma (Giudice et al., 2021; Kakumoto, 2024). Although these areas differ from chronic kidney disease, they demonstrate a common scientific direction: clinical decisions are increasingly informed by predictive markers, computational modeling, and individualized risk profiles. In the present study, the integration of XGBoost and SHAP-based explainability provided a similar precision-oriented framework for quality-of-life prediction in chronic kidney disease, allowing the identification of both high-risk patients and the factors most responsible for their predicted risk. This is important because a model that simply classifies patients has limited clinical value unless clinicians can understand why a specific prediction was made and which modifiable or monitorable factors should be addressed.

5. Conclusion

Overall, the results suggest that low quality of life among patients with chronic kidney disease is best understood as the outcome of interacting physiological, clinical, treatment-related, and psychosocial factors. The high predictive performance of XGBoost indicates that machine learning can effectively model this complexity, while SHAP analysis demonstrates that the model's decisions were clinically interpretable and aligned with known disease mechanisms. The findings support a patient-centered approach in which quality of life is assessed alongside kidney function, anemia, nutritional status, mineral metabolism, dialysis exposure, cardiovascular disease, and comorbidity burden. By

identifying patients at high risk for low quality of life, clinicians may be able to intervene earlier through multidisciplinary care, symptom management, psychosocial support, nutritional optimization, anemia treatment, cardiovascular risk reduction, and individualized treatment planning. Therefore, the present study adds to the growing evidence that explainable machine learning can support clinical decision-making in chronic kidney disease by combining predictive accuracy with transparent interpretation.

6. Limitations & Suggestions

This study had several limitations that should be considered when interpreting the findings. First, the cross-sectional design limited the ability to infer causal relationships between predictors and low quality of life. Although the machine learning model identified important variables associated with low quality of life, it could not determine whether these factors directly caused deterioration in quality of life or whether they reflected broader disease severity. Second, the sample was recruited from Tehran, which may limit the generalizability of the findings to patients in other cities, rural areas, or healthcare systems with different clinical resources and socioeconomic conditions. Third, although the sample size was adequate for the planned analysis, larger multicenter datasets would provide greater statistical power and model stability. Fourth, some potentially relevant variables, such as detailed psychological symptoms, social support, physical activity, dietary adherence, sleep quality, inflammatory markers, and longitudinal treatment changes, were not included. Finally, although SHAP analysis improved interpretability, explainable artificial intelligence methods still depend on the quality of the underlying data and should not be interpreted as proof of causal mechanisms.

Future studies should use longitudinal designs to examine whether the predictors identified in this study can forecast changes in quality of life over time. Multicenter studies with larger and more diverse samples are recommended to externally validate the XGBoost model and determine whether its performance remains stable across different populations, treatment settings, and stages of chronic kidney disease. Future research should also compare additional machine learning approaches, including ensemble stacking, neural networks, survival models, and time-series prediction methods, particularly when repeated clinical measurements are available. It would also be valuable to include more comprehensive psychosocial, behavioral, and environmental variables, such as depression, anxiety, perceived stress, social support, sleep quality, physical activity, health literacy, and treatment adherence. Finally, future studies should evaluate whether integrating explainable machine learning models into clinical workflows improves decision-making, patient monitoring, referral patterns, and quality-of-life outcomes.

The findings of this study suggest that clinicians should assess quality of life as a routine component of chronic kidney disease care rather than treating it as a secondary outcome. Patients with longer disease duration, dialysis treatment, lower eGFR, anemia, low albumin, higher phosphorus, cardiovascular disease, multiple comorbidities, and high medication burden should be considered at elevated risk for low quality of life and should receive closer monitoring. Healthcare teams should use risk prediction not as a replacement for clinical judgment but as a supportive tool for identifying patients who may benefit from additional assessment and intervention. Practical care strategies may include early referral to multidisciplinary teams, nutritional counseling, anemia management, cardiovascular risk control, symptom management, psychological support, patient education, and individualized care planning. The use of explainable prediction models may help clinicians communicate risk more clearly, prioritize modifiable factors, and design more patient-centered interventions for individuals living with chronic kidney disease.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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