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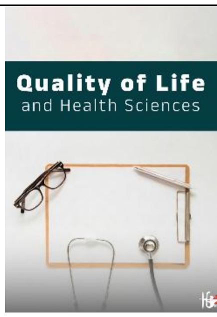

LightGBM-Based Prediction of Poor Quality of Life Among Patients With Heart Failure Using Clinical, Behavioral, and Psychological Features

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ABSTRACT

Objective: This study aimed to develop and interpret a LightGBM-based machine learning model for predicting poor quality of life among patients with heart failure using clinical, behavioral, and psychological features.
Methods and Materials: This multicenter cross-sectional predictive modeling study was conducted among 428 patients with heart failure recruited from cardiology outpatient clinics and heart failure units in Sweden. Clinical data included left ventricular ejection fraction, NYHA functional class, duration of heart failure, comorbidities, hospitalization history, blood pressure, heart rate, and medication-related indicators. Behavioral variables included physical activity, sleep quality, and heart failure self-care behaviors. Psychological variables included depressive symptoms, anxiety symptoms, perceived stress, and perceived social support. Quality of life was assessed using the Kansas City Cardiomyopathy Questionnaire, and poor quality of life was defined as an overall summary score below 50. The dataset was divided into training and testing subsets, and an optimized LightGBM model was developed using cross-validation and hyperparameter tuning. Model performance was evaluated using AUC, accuracy, sensitivity, specificity, precision, F1-score, balanced accuracy, and Brier score. SHAP analysis was used for model interpretation.
Findings: Poor quality of life was identified in 174 patients, representing 40.7% of the sample. Compared with patients without poor quality of life, patients with poor quality of life had significantly lower left ventricular ejection fraction, higher NYHA class, longer disease duration, higher comorbidity burden, more previous heart failure hospitalization, lower physical activity, poorer sleep quality, weaker self-care, higher depression, higher anxiety, higher perceived stress, and lower perceived social support. The optimized LightGBM model achieved strong predictive performance in the test set, with an AUC of 0.859, accuracy of 0.806, sensitivity of 0.788, specificity of 0.818, F1-score of 0.764, balanced accuracy of 0.803, and Brier score of 0.137. SHAP analysis identified depressive symptoms, NYHA functional class, sleep quality, anxiety symptoms, previous hospitalization, self-care maintenance, physical activity, ejection fraction, perceived stress, and social support as the most influential predictors.
Conclusion: The LightGBM model demonstrated strong ability to predict poor quality of life among patients with heart failure and showed that quality-of-life impairment is influenced by a combination of clinical severity, behavioral limitations, sleep disturbance, psychological distress, and reduced social support.
Keywords: *Heart failure; quality of life; LightGBM; machine learning; depression; anxiety; sleep quality; self-care; SHAP; predictive modeling.*

1. Introduction

Heart failure is a chronic, progressive, and clinically heterogeneous cardiovascular syndrome that affects patients far beyond the boundaries of cardiac function alone. Although traditional clinical evaluation has relied heavily on indicators such as ventricular function, symptom severity, hospitalization history, and functional class, contemporary cardiovascular care increasingly recognizes that patient-reported outcomes are essential for understanding the real burden of disease. Quality of life is particularly important in heart failure because patients often live with persistent dyspnea, fatigue, reduced physical capacity, recurrent medical visits, polypharmacy, uncertainty about prognosis, and limitations in social and occupational functioning. In this context, poor quality of life is not merely a secondary consequence of disease severity but a central clinical outcome that reflects the interaction between physiological impairment, behavioral adaptation, psychological distress, and available social resources. Evidence from cardiac populations has shown that patient-reported outcomes are strongly related to perceived functioning, symptom burden, treatment experience, and emotional adjustment, supporting the need to place quality of life at the center of cardiovascular assessment and care (Liu et al., 2022; Lu, 2022; Pawlak et al., 2024; Wungouw, 2021).

The multidimensional nature of quality of life in cardiovascular disease has led to growing interest in biopsychosocial models of cardiac care. Cardiovascular diseases are increasingly understood as conditions in which biological mechanisms, psychological states, social context, and health behaviors interact continuously. Reviews of cardiovascular disease and psychiatric disorders have emphasized that mental health problems are common among cardiac patients and may influence symptom perception, adherence, rehabilitation participation, treatment burden, and long-term adjustment (Parlati et al., 2024; Topuz & Topuz, 2024). Broader discussions of psychosocial issues in medical care have similarly argued that clinical outcomes cannot be fully understood without considering distress, coping, illness beliefs, demoralization, and interpersonal support (Fava et al., 2024). The integration of clinical psychology into cardiovascular services has therefore been proposed as an important step toward improving patient-centered outcomes among adults with cardiovascular disease (Smolderen et al., 2024). This perspective is also consistent with evidence from medically compromised populations showing that psychological background, emotional vulnerability, and chronic illness experience can shape health-related functioning and patient engagement with care (Abiko et al., 2021).

Among the psychological factors associated with cardiovascular outcomes, depression and anxiety have received particular attention. Depression is highly relevant to heart failure because it may reduce motivation for self-care, diminish physical activity, worsen fatigue, impair sleep, increase symptom vigilance, and intensify perceived disability. Biological and behavioral pathways linking depression and cardiovascular disease include autonomic dysregulation, inflammation, endocrine stress responses, sedentary behavior, and reduced adherence to treatment recommendations (Garrels et al., 2023; Sobolewska-Nowak et al., 2023). Anxiety is also clinically important because it can amplify perceived cardiac symptoms, increase health-related fear, interfere with decision-making, and reduce confidence in self-management. Observational work in cardiovascular and primary care settings has demonstrated meaningful associations among anxiety, emotional dysregulation, hypertension, and self-care, suggesting that emotional regulation is an important component of cardiovascular health behavior (Giacomo et al., 2023). Anxiety and depression have also been examined in relation to valvular disease, cardiac rehabilitation, acute coronary syndrome, myocardial infarction, and psycho-cardiology interventions, further supporting the relevance of psychological symptoms across the cardiovascular disease spectrum (Chen et al., 2023; Gostoli et al., 2021; Martínez, 2023; Moran et al., 2021).

In patients with heart failure, psychological distress is especially consequential because it often occurs alongside severe physical symptoms and functional limitation. Patients may experience fear of deterioration, uncertainty about disease progression, concerns about dependence, and frustration related to reduced autonomy. These experiences can intensify perceived illness burden even when objective clinical markers are relatively stable. Research on psychosocial interventions for heart failure has shown that depression, anxiety, and quality of life are modifiable targets and that psychological interventions may contribute to improvements in emotional and functional outcomes (Chernoff, 2022). Cognitive-behavioral therapy has been discussed as a potentially useful intervention for heart failure patients because it addresses maladaptive beliefs, activity avoidance, emotional distress, and coping patterns that may affect daily functioning (Katta et al., 2023). Mind–body interventions have also been examined in heart failure, reflecting increasing recognition that psychological regulation, relaxation, attention, and embodied self-awareness may contribute to symptom management and well-being (Suksatan & Tankumpuan, 2021). These findings suggest that psychological variables should not be treated as peripheral covariates in heart failure research but as major predictors of quality of life.

Behavioral features are equally important in explaining quality of life among patients with heart failure. Self-care behaviors, including medication adherence, symptom monitoring, dietary regulation, fluid management, and timely response to worsening symptoms, are central to disease control. Physical activity and rehabilitation participation can improve functional capacity and perceived vitality, whereas inactivity may reinforce deconditioning, fatigue, and dependency. The relationship between physical exercise and quality of life in cardiac patients supports the inclusion of behavioral indicators in prediction models that aim to identify patients with poor perceived health status (Wungouw, 2021). Cardiovascular rehabilitation may also influence psychophysiological stress and broader adaptation processes, indicating that behavioral intervention can have effects beyond physical conditioning alone (Wagner-Skacel et al., 2021). Related evidence on forest therapy and other restorative interventions suggests that structured exposure to supportive environments may have physiological and psychological benefits, reinforcing the broader principle that behavioral and environmental factors can influence health-related quality of life (Yi et al., 2022). Therefore, prediction of poor quality of life in heart failure should include not only clinical markers but also behavioral patterns that reflect how patients manage and live with their condition.

Sleep disturbance represents another major contributor to poor quality of life in heart failure. Insomnia and poor sleep quality are common among patients with heart failure and may result from dyspnea, nocturia, medication effects, anxiety, depression, pain, hospitalization experiences, or irregular daily routines. Sleep impairment can worsen fatigue, reduce daytime functioning, increase emotional reactivity, and weaken capacity for self-care. Recent discussions of insomnia in heart failure have emphasized its causes, consequences, and potential interventions, highlighting sleep as both a symptom domain and a therapeutic target (Atay & Çiftçi, 2025). Expert opinion on the management of patients with heart failure and selected mental disorders has also recognized sleep disorders as clinically important, alongside depression, anxiety, and delirium (Pawlak et al., 2024). Because poor sleep can interact with depressive symptoms, physical inactivity, and perceived stress, it may be a particularly valuable predictor in machine learning models designed to identify patients at risk of poor quality of life.

Stress, trauma-related symptoms, and coping strategies further complicate the relationship between cardiovascular disease and quality of life. Acute cardiac events, recurrent hospitalizations, device implantation, arrhythmia episodes, and perceived threat of death can produce psychological sequelae that resemble traumatic stress. Posttraumatic stress disorder has been described as a possible consequence of acute cardiovascular disease, and cardiac disease-induced trauma may affect emotional functioning, vigilance, avoidance, and long-term adaptation (Princip et al., 2024; Princip et al., 2023). Coping style is also relevant because patients who rely on disengaged, avoidant, or emotion-focused strategies may experience greater distress than those who use active and engaged coping approaches (Sowan et al., 2026). In cardiac device and arrhythmia populations, psychosocial symptoms have been linked to patient-reported outcomes and the need for integrated clinical assessment (Sandhu et al., 2021; Särnholm et al., 2025). Social comparison processes among cardiac patients with defibrillator experience may also shape adaptation, perceived vulnerability, and psychological distress (Willy et al., 2024). Preprocedural anxiety in adults with congenital heart disease and depressive or anxious symptoms among patients receiving cardiac resynchronization therapy further demonstrate that emotional burden is common across diverse cardiovascular contexts (Cook et al., 2023; Florou et al., 2025).

Evidence from congenital and lifelong cardiac conditions also supports the importance of psychological and quality-of-life assessment. Scientific statements and multinational studies in congenital heart disease have emphasized that psychological outcomes, patient-reported functioning, and psychosocial interventions are essential components of comprehensive care (Kovacs et al., 2022; Lu, 2022). In children and adolescents with congenital heart disease, psychological and health-related quality-of-life status are influenced by multiple factors, demonstrating that cardiac illness affects developmental, emotional, and social domains as well as physical health (Liu et al., 2022). Although the clinical course of adult heart failure differs from congenital heart disease, both conditions show that cardiac diagnoses can reshape identity, autonomy, social participation, and perceived future possibilities. Similar lessons can be drawn from other chronic progressive diseases, such as Duchenne muscular dystrophy, where physical impairment intersects with cognitive, psychopathological, and psychosocial resources in determining lived experience (Tizzoni et al., 2025). Cognitive impairment and psychopathology after out-of-hospital cardiac arrest also demonstrate that cardiovascular events may have persistent neuropsychological and emotional consequences that influence recovery and functioning (Wagner et al., 2020).

The biological mechanisms linking psychological distress and cardiovascular outcomes are complex and bidirectional. Depression, anxiety, sleep disturbance, and stress may influence inflammatory activity, autonomic balance, neuroendocrine regulation, endothelial function, and health behavior. Conversely, cardiac symptoms, reduced perfusion, medication effects, disability, and recurrent medical crises can contribute to emotional distress. Emerging psycho-cardiology perspectives have begun to examine novel mechanisms and treatment opportunities, including the gut microbiome as a potential pathway in psycho-cardiologic disease (Fang et al., 2025). Pharmacological and cardiovascular therapeutic perspectives have also considered the possibility that cardiovascular pathways may overlap with mechanisms relevant to anxiety treatment (Repova et al., 2022). Training models in cardiac psychology further show that integrated psychosocial care requires specialized knowledge and practical implementation within cardiovascular settings (Sall et al., 2022). These developments support a shift away from isolated risk-factor thinking toward multidomain assessment that captures clinical, behavioral, and psychological determinants simultaneously.

Despite increasing recognition of these interconnections, routine clinical practice still faces difficulty identifying which patients with heart failure are most likely to experience poor quality of life. Traditional statistical approaches can test selected associations, but they may be limited when predictors are numerous, correlated, nonlinear, or interactive. Poor quality of life may emerge not from one dominant risk factor but from a pattern in which moderate depressive symptoms, sleep disturbance, low activity, advanced functional class, weak self-care, and reduced support combine to produce high vulnerability. Machine learning methods are well suited to this type of prediction problem because they can model complex relationships among heterogeneous variables and generate individualized risk estimates. LightGBM, as a gradient boosting framework based on decision trees, is particularly useful for structured clinical datasets because it can handle nonlinear associations, interactions, variable imbalance, and mixed predictor types while maintaining strong predictive performance. However, prediction alone is insufficient in clinical research; interpretable modeling is needed so that clinicians can understand which features contribute most strongly to risk classification and how those features influence predicted probability.

For heart failure research, an interpretable LightGBM model may provide a practical bridge between patient-centered assessment and clinical decision support. By combining clinical indicators such as functional class, ejection fraction, hospitalization history, and comorbidity with behavioral features such as physical activity, sleep, and self-care, and psychological features such as depression, anxiety, perceived stress, coping, and social support, such a model can reflect the real-world complexity of quality of life impairment. This approach is aligned with the broader movement toward integrated cardiovascular care, in which cardiologists, nurses, psychologists, rehabilitation specialists, and primary care providers collaborate to address both disease management and lived experience (Fava et al., 2024; Smolderen et al., 2024). It also responds to evidence that psychosocial interventions, behavioral regulation, and psychological support can influence quality of life and distress among patients with cardiac disease (Chernoff, 2022; Katta et al., 2023; Suksatan & Tankumpuan, 2021). Therefore, a predictive model that identifies the most influential clinical, behavioral, and psychological contributors to poor quality of life may help clinicians prioritize comprehensive assessment, early supportive intervention, and individualized care planning.

The aim of this study was to develop and interpret a LightGBM-based predictive model for poor quality of life among patients with heart failure using clinical, behavioral, and psychological features.

2. Methods and Materials

2.1. Study Design and Participants

This study was designed as a multicenter, cross-sectional predictive modeling study conducted among patients with heart failure in Sweden. Participants were recruited from cardiology outpatient clinics and heart failure units affiliated with university and regional hospitals in Stockholm, Uppsala, and Gothenburg. The target population consisted of adult patients with a confirmed clinical diagnosis of heart failure who were receiving routine follow-up care during the study period. A total of 428 patients with heart failure were included in the final analysis after eligibility screening and removal of incomplete records. Patients were eligible for inclusion if they were 18 years of age or older, had a documented diagnosis of heart failure according to clinical records, had been clinically stable for at least four weeks before recruitment, and were able to complete the study questionnaires independently or with minimal assistance. Patients with acute decompensated heart failure at the time of data collection, severe cognitive impairment, active psychotic disorder, terminal illness unrelated to heart failure, or missing outcome data on quality of life were excluded from the study. All participants received written and verbal information about the purpose and procedures of the study, and written informed consent was obtained before participation.

2.2. Measures

Clinical and demographic data were collected using a structured patient information form developed for the present study. The form included age, sex, marital status, educational level, employment status, body mass index, duration of heart failure, New York Heart Association functional class, left ventricular ejection fraction, heart failure phenotype, systolic and diastolic blood pressure, resting heart rate, history of hospitalization due to heart failure during the previous year, comorbid conditions, medication profile, smoking status, and relevant laboratory indicators when available in the medical record. Clinical variables were extracted from electronic medical records by trained research staff and verified for consistency before entry into the analytical dataset. Behavioral characteristics were assessed through patient self-report and included physical activity, sleep quality, medication adherence, dietary self-care, alcohol consumption, and smoking behavior. Physical activity was assessed using the short form of the International Physical Activity Questionnaire, which estimates activity level across walking, moderate activity, and vigorous activity domains. Sleep quality was assessed using the Pittsburgh Sleep Quality Index, which evaluates subjective sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. Heart failure self-care behaviors were assessed using the Self-Care of Heart Failure Index, which measures self-care maintenance, symptom perception, and self-care management behaviors among patients with heart failure.

Psychological features were measured using standardized self-report instruments. Depressive symptoms were assessed using the Patient Health Questionnaire-9, which consists of nine items evaluating the frequency of depressive symptoms during the previous two weeks. Anxiety symptoms were assessed using the Generalized Anxiety Disorder-7 scale, which measures core symptoms of generalized anxiety and provides a continuous severity score. Perceived stress was measured using the Perceived Stress Scale-10, which evaluates the extent to which individuals perceive their life situations as unpredictable, uncontrollable, and overloaded. Perceived social support was assessed using the Multidimensional Scale of Perceived Social Support, which evaluates support from family, friends, and significant others. Health-related quality of life, which served as the outcome variable, was measured using the Kansas City Cardiomyopathy Questionnaire. The questionnaire assesses heart failure-related quality of life across domains such as physical limitation, symptom burden, quality of life, social limitation, and overall health status. For predictive modeling, poor quality of life was defined as a Kansas City Cardiomyopathy Questionnaire overall summary score below 50, indicating markedly impaired health status and substantial burden of heart failure symptoms and limitations.

2.3. Data Analysis

Data analysis was performed in several sequential stages, including data preparation, descriptive analysis, model development, model evaluation, and model interpretation. Initially, all variables were screened for completeness, distributional characteristics, outliers, and logical inconsistencies. Continuous variables were summarized using means and standard deviations or medians and interquartile ranges depending on their distribution, whereas categorical variables were summarized using frequencies and percentages. Missing data were examined to determine their extent and pattern. Variables with excessive missingness were excluded from the predictive modeling process, while variables with acceptable levels of missingness were handled using appropriate imputation procedures. Continuous predictors were retained in their original scale when suitable, and categorical predictors were encoded for machine learning analysis. The outcome variable was binary and represented poor versus non-poor quality of life according to the predefined Kansas City Cardiomyopathy Questionnaire threshold.

A Light Gradient Boosting Machine model was developed to predict poor quality of life among patients with heart failure using clinical, behavioral, and psychological predictors. The dataset was randomly divided into training and testing subsets, with 70% of the sample used for model training and 30% reserved for final model evaluation. Stratified sampling was applied during data partitioning to preserve the distribution of the outcome variable across both subsets. Hyperparameter tuning was conducted within the training data using cross-validation. The main tuned parameters included number of estimators, learning rate, maximum tree depth, number of leaves, minimum data in leaf, feature fraction, bagging fraction, and regularization parameters. Model performance was evaluated on the independent testing dataset using the area under the receiver operating characteristic curve, accuracy, sensitivity, specificity, precision, F1-score, and balanced accuracy. Calibration was assessed by comparing predicted probabilities with observed outcome frequencies, and overall model reliability was examined to ensure that the model provided clinically meaningful risk estimates rather than only class predictions.

To enhance interpretability, feature importance was examined using both gain-based importance and SHAP values. SHAP analysis was used to identify the direction and relative contribution of the most influential predictors of poor quality of life. Clinical, behavioral, and psychological variables were interpreted together to determine whether poor quality of life was mainly associated with disease severity indicators, lifestyle and self-care behaviors, psychological distress, or a combination of these domains. All analyses were performed using Python-based machine learning libraries. Statistical and predictive modeling procedures were conducted with attention to reproducibility, including fixed random seeds, standardized preprocessing procedures, and separation of training and testing data to reduce the risk of data leakage.

3. Findings and Results

A total of 428 patients with heart failure were included in the final analytical sample. The mean age of the participants was 68.4 years with a standard deviation of 10.9 years, and the age range was 38 to 91 years. Of the total sample, 261 participants were men, representing 61.0% of the sample, and 167 participants were women, representing 39.0%. Most participants were married or living with a partner, and a large proportion were retired, which was consistent with the older age structure of the heart failure population. Regarding educational status, the sample included patients with primary, secondary, vocational, and university-level education, reflecting a clinically heterogeneous outpatient population. Participants were recruited from heart failure clinics in Stockholm, Uppsala, and Gothenburg, with the largest proportion recruited from Stockholm-based centers. Based on the predefined Kansas City Cardiomyopathy Questionnaire cut-off score, 174 patients, equal to 40.7% of the sample, were classified as having poor quality of life, while 254 patients, equal to 59.3% of the sample, were classified as having non-poor quality of life. The mean overall quality of life score was 57.6 with a standard deviation of 21.4, indicating that the sample included patients across a wide spectrum of perceived health status, symptom burden, and functional limitation.

Table 1

Clinical, Behavioral, and Psychological Characteristics of Patients According to Quality of Life Status

Variable	Poor quality of life (n = 174)	Non-poor quality of life (n = 254)	Test statistic	p-value
Left ventricular ejection fraction, mean ± SD	38.1 ± 10.8	44.6 ± 11.9	t = -5.72	< .001
NYHA class III–IV, n (%)	119 (68.4)	64 (25.2)	χ^2 = 78.94	< .001
Heart failure hospitalization in previous year, n (%)	79 (45.4)	54 (21.3)	χ^2 = 28.43	< .001
Duration of heart failure in years, mean ± SD	7.8 ± 4.6	5.9 ± 3.8	t = 4.66	< .001
Comorbidity index score, mean ± SD	4.2 ± 1.8	3.1 ± 1.5	t = 6.63	< .001
Resting heart rate, mean ± SD	78.5 ± 12.7	72.4 ± 11.9	t = 5.08	< .001
Physical activity, MET-min/week, mean ± SD	612.8 ± 394.5	1018.6 ± 526.9	t = -8.61	< .001
Pittsburgh Sleep Quality Index score, mean ± SD	9.8 ± 3.6	6.0 ± 3.1	t = 11.69	< .001
Self-care maintenance score, mean ± SD	55.9 ± 15.7	67.4 ± 14.2	t = -7.88	< .001
Self-care management score, mean ± SD	50.7 ± 16.4	62.8 ± 15.1	t = -7.89	< .001
PHQ-9 depression score, mean ± SD	13.1 ± 5.4	6.7 ± 4.2	t = 13.80	< .001
GAD-7 anxiety score, mean ± SD	9.7 ± 4.8	5.1 ± 3.7	t = 11.15	< .001
Perceived Stress Scale score, mean ± SD	22.4 ± 6.1	16.2 ± 5.8	t = 10.62	< .001
Multidimensional Scale of Perceived Social Support score, mean ± SD	43.8 ± 13.6	55.6 ± 12.8	t = -9.13	< .001

As shown in Table 1, patients with poor quality of life demonstrated a more unfavorable clinical, behavioral, and psychological profile compared with patients whose quality of life was not classified as poor. Clinically, poor quality of life was associated with lower left ventricular ejection fraction, more advanced NYHA functional class, longer duration of heart failure, higher comorbidity burden, higher resting heart rate, and a greater likelihood of hospitalization due to heart failure during the previous year. These findings indicate that patients with poorer perceived quality of life were not only more symptomatic but also had a heavier disease burden and greater clinical instability. Behavioral differences were also substantial. Patients with poor quality of life reported significantly lower physical activity levels, poorer sleep quality, and weaker heart failure self-care maintenance and management behaviors. The psychological profile of the poor quality of life group was particularly distinct, with significantly higher depressive symptoms, anxiety symptoms, and perceived stress, alongside significantly lower perceived social support. Overall, the group comparisons showed that poor quality of life among patients with heart failure was not explained by a single clinical indicator but was instead associated with a multidimensional pattern involving disease severity, reduced self-care capacity, impaired sleep, low activity, psychological distress, and reduced interpersonal support.

Table 2

Predictive Performance of the Optimized LightGBM Model for Poor Quality of Life

Performance index	Cross-validation result	Test set result
Area under the ROC curve	0.872 ± 0.026	0.859
Accuracy	0.802 ± 0.031	0.806
Sensitivity	0.781 ± 0.044	0.788
Specificity	0.816 ± 0.039	0.818
Precision	0.751 ± 0.047	0.742
Negative predictive value	0.837 ± 0.035	0.851
F1-score	0.766 ± 0.038	0.764
Balanced accuracy	0.799 ± 0.034	0.803
Brier score	0.142 ± 0.018	0.137

Table 2 presents the predictive performance of the optimized LightGBM model after training, cross-validation, and final testing. The model demonstrated strong discriminatory ability, with an area under the ROC curve of 0.872 during cross-validation and 0.859 in the independent test set. This indicates that the model was able to distinguish patients with poor quality of life from those without poor quality of life with a high degree of accuracy. The test set accuracy was 0.806, showing that approximately four out of five patients were correctly classified. Sensitivity was 0.788, indicating that the model correctly identified most patients who had poor quality of life, while specificity was 0.818, indicating strong ability to correctly classify patients who did not have poor quality of life. The precision value of 0.742 suggested that most patients predicted as having poor quality of life were true positive cases, while the negative predictive value of 0.851 indicated that patients classified as not having poor quality of life were very likely to be correctly identified. The F1-score of 0.764 reflected an acceptable balance between precision and sensitivity. The Brier score of 0.137 further indicated that the predicted probabilities were reasonably calibrated and that the model did not merely provide accurate classifications but also generated clinically meaningful probability estimates. Overall, the results support the usefulness of LightGBM as a predictive approach for identifying heart failure patients at increased risk of poor quality of life.

Table 3

Most Important Predictors of Poor Quality of Life Based on SHAP Analysis

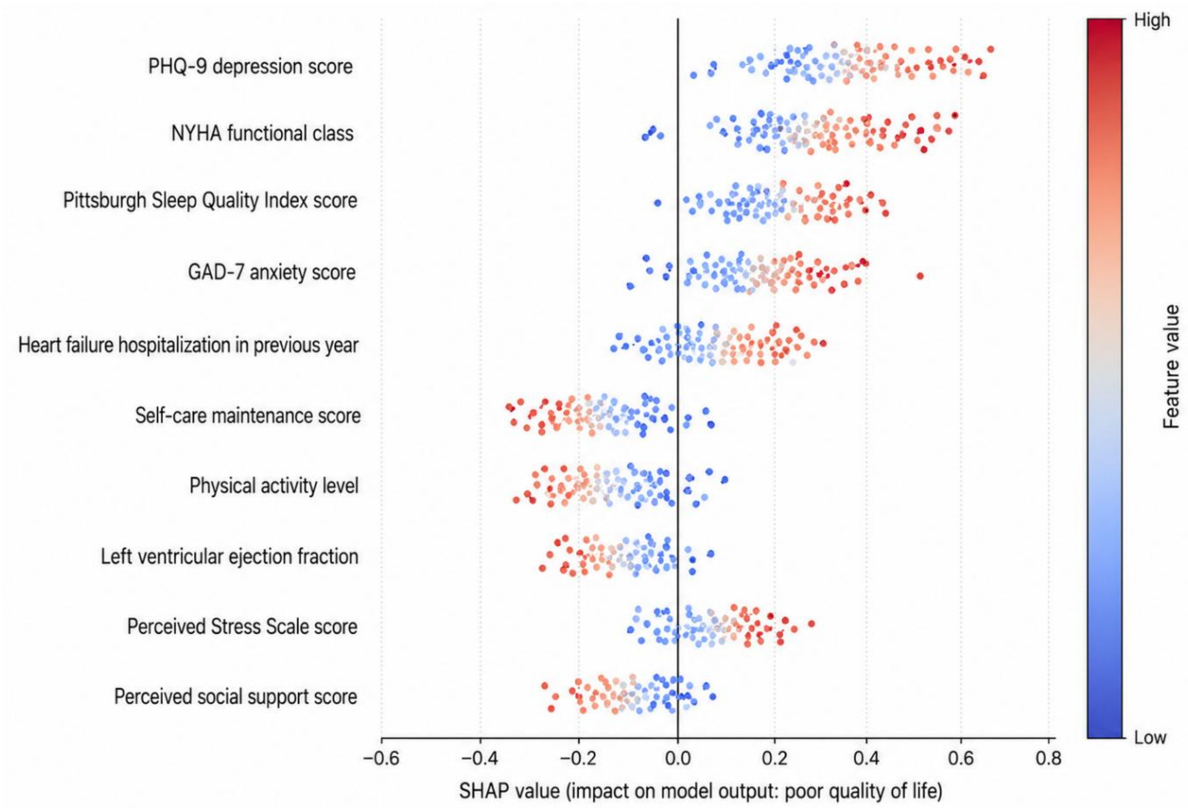
Rank	Predictor	Mean absolute SHAP value	Direction of association with poor quality of life
1	PHQ-9 depression score	0.091	Higher depressive symptoms increased predicted risk
2	NYHA functional class	0.079	Higher functional class increased predicted risk
3	Pittsburgh Sleep Quality Index score	0.073	Poorer sleep quality increased predicted risk

4	GAD-7 anxiety score	0.062	Higher anxiety symptoms increased predicted risk
5	Heart failure hospitalization in previous year	0.055	Previous hospitalization increased predicted risk
6	Self-care maintenance score	0.047	Lower self-care maintenance increased predicted risk
7	Physical activity level	0.041	Lower physical activity increased predicted risk
8	Left ventricular ejection fraction	0.039	Lower ejection fraction increased predicted risk
9	Perceived Stress Scale score	0.035	Higher perceived stress increased predicted risk
10	Perceived social support score	0.031	Lower social support increased predicted risk

Table 3 shows the relative importance of the strongest predictors in the optimized LightGBM model based on SHAP analysis. Depressive symptoms emerged as the most influential predictor of poor quality of life, suggesting that psychological distress had a central role in distinguishing patients with severe quality of life impairment. NYHA functional class was the second most important predictor, indicating that functional limitation remained a core clinical determinant of poor quality of life among patients with heart failure. Sleep quality was the third strongest predictor, showing that subjective sleep disturbance contributed substantially to the prediction of quality of life status. Anxiety symptoms and previous hospitalization due to heart failure also had strong predictive effects, suggesting that emotional burden and recent clinical instability were important indicators of vulnerability. Self-care maintenance and physical activity were also among the most influential predictors, indicating that behavioral factors contributed meaningfully to the model beyond clinical severity and psychological distress. Lower left ventricular ejection fraction, higher perceived stress, and lower perceived social support completed the top ten predictors. Taken together, the SHAP findings demonstrate that the prediction of poor quality of life was driven by an interaction of psychological symptoms, functional impairment, sleep disturbance, previous hospitalization, self-care behavior, physical activity, cardiac function, stress, and social support. This pattern confirms that poor quality of life in heart failure is a multidimensional outcome and that machine learning models can capture clinically relevant risk patterns that extend beyond traditional biomedical indicators.

Figure 1

SHAP Summary Plot of Feature Effects in the LightGBM Model Predicting Poor Quality of Life Among Patients With Heart Failure



The SHAP summary plot demonstrated the direction and magnitude of feature effects across individual patients. Higher values of depressive symptoms, NYHA functional class, sleep disturbance, anxiety symptoms, previous hospitalization, and perceived stress shifted predictions toward poor quality of life, whereas higher self-care maintenance, greater physical activity, higher left ventricular ejection fraction, and stronger perceived social support shifted predictions away from poor quality of life. The figure also suggested nonlinear patterns in several predictors. For example, depressive symptom scores above the moderate range had a particularly strong positive effect on the probability of poor quality of life, while very low physical activity and weak self-care scores showed marked risk-enhancing effects. Similarly, patients with advanced functional limitation and poor sleep quality were consistently placed at higher predicted risk. The figure therefore reinforces the main model interpretation by showing that clinical severity alone did not determine the prediction. Instead, the probability of poor quality of life increased most clearly when functional impairment was accompanied by psychological distress, sleep problems, poor self-care, low activity, and limited social support. This visual explanation supports the clinical interpretability of the LightGBM model and shows how individual-level prediction can be used to identify patients who may require more comprehensive assessment and targeted supportive interventions.

4. Discussion

The present study examined the prediction of poor quality of life among patients with heart failure using a LightGBM model based on clinical, behavioral, and psychological features. The findings showed that poor quality of life was common in the sample, with 40.7% of patients classified as having poor quality of life according to the predefined Kansas City Cardiomyopathy Questionnaire threshold. Patients in the poor quality of life group had a more adverse clinical profile, including lower left ventricular ejection fraction, more advanced NYHA functional class, longer heart failure duration, higher comorbidity burden, higher resting heart rate, and more frequent heart failure hospitalization during the previous year. These results confirm that poor quality of life in heart failure remains closely linked to disease severity and functional limitation. However, the findings also showed that clinical variables alone did not fully characterize the poor quality of life group. Patients with poor quality of life also reported lower physical activity, poorer sleep quality, weaker self-care maintenance and management, higher depressive symptoms, higher anxiety symptoms, higher perceived stress, and lower perceived social support. This pattern supports the biopsychosocial view of cardiovascular disease, according to which cardiac outcomes and patient-reported health status are shaped by the interaction of biological disease burden, behavioral functioning, emotional distress, and social context (Fava et al., 2024; Parlati et al., 2024; Smolderen et al., 2024; Topuz & Topuz, 2024).

The predictive performance of the optimized LightGBM model was strong, with an area under the ROC curve of 0.859 in the independent test set, accuracy of 0.806, sensitivity of 0.788, specificity of 0.818, F1-score of 0.764, and balanced accuracy of 0.803. These findings indicate that the model was able to distinguish patients with poor quality of life from those with non-poor quality of life with clinically meaningful discrimination. The sensitivity value suggests that the model successfully identified a large proportion of patients experiencing poor quality of life, while the specificity value indicates that it also avoided excessive false positive classification. This balance is important in heart failure care because under-identification may leave vulnerable patients without psychological, behavioral, or rehabilitative support, whereas over-identification may create unnecessary clinical workload. The acceptable Brier score further suggested that the model provided reasonably reliable probability estimates rather than only binary classifications. These results are consistent with the growing emphasis on patient-reported outcomes in cardiovascular care and reinforce the need for predictive systems capable of integrating medical and psychosocial data (Kovacs et al., 2022; Liu et al., 2022; Lu, 2022; Pawlak et al., 2024).

The SHAP analysis identified depressive symptoms as the most influential predictor of poor quality of life. This finding is highly consistent with prior cardiovascular research showing that depression is not only common among patients with cardiac disease but also deeply connected to perceived health, functional limitation, treatment engagement, and recovery experience. Depression may worsen quality of life through several pathways, including reduced motivation for self-care, decreased physical activity, impaired sleep, greater fatigue, hopelessness, reduced social engagement, and heightened perception of somatic symptoms. Previous research has described shared pathways between depression and cardiovascular disease, including psychophysiological stress, inflammation, autonomic dysregulation, and behavioral mechanisms (Garrels et al., 2023; Sobolewska-Nowak et al., 2023). The importance of depression in the present model is also aligned with evidence supporting psychosocial and cognitive-behavioral interventions for patients with heart failure and other cardiac conditions, where reductions in depression and emotional distress may contribute to improvements in quality of life (Chen et al., 2023; Chernoff, 2022; Gostoli et al., 2021; Katta et al., 2023).

NYHA functional class emerged as the second most important predictor, confirming that subjective and observable functional impairment remains a central determinant of quality of life in heart failure. Patients with more advanced functional class experience greater limitation in daily activities, reduced tolerance for exertion, more frequent symptoms, and greater dependence on others, all of which can directly reduce perceived quality of life. This finding also explains why clinical severity variables such as hospitalization history and lower ejection fraction contributed to the model. Heart failure hospitalization in the previous year was among the strongest predictors, suggesting that recent clinical instability carries psychological and functional consequences beyond the acute medical event. Hospitalization may increase fear of deterioration, disrupt routines, reduce confidence in self-management, and heighten awareness of disease progression. These results are consistent with literature describing the psychological burden of cardiac disease, including trauma-related symptoms after acute cardiovascular events and stress-related responses to cardiac illness (Princip et al., 2024; Princip et al., 2023). The role of clinical severity is also consistent with studies of congenital and chronic cardiac populations in which heart failure status and patient-reported outcomes are closely intertwined (Kovacs et al., 2022; Lu, 2022).

Sleep quality was the third most influential feature in the model, and patients with poor quality of life had substantially higher Pittsburgh Sleep Quality Index scores. This result highlights sleep disturbance as a key component of the lived experience of heart failure. Insomnia and poor sleep may reflect nocturnal symptoms, breathing discomfort, anxiety, depressive rumination, medication effects, nocturia, or reduced physical activity, but they also independently contribute to fatigue, cognitive difficulties, irritability, and reduced daytime functioning. The strong role of sleep in the model aligns with recent work emphasizing insomnia in heart failure, including its causes, consequences, and possible interventions (Atay & Çiftçi, 2025). It is also consistent with expert recommendations that sleep disorders should be assessed together with depression and anxiety in patients with heart failure (Pawlak et al., 2024). In practical terms, the finding suggests that poor sleep may be one of the most clinically accessible signals of declining quality of life, particularly because sleep complaints are often identifiable during routine nursing or outpatient encounters.

Anxiety symptoms were also a major predictor of poor quality of life. This finding is understandable because anxiety can intensify cardiac symptom monitoring, increase fear of physical exertion, reduce confidence in self-care, and amplify concerns about hospitalization, arrhythmia, device therapy, or sudden deterioration. Previous cardiovascular studies have emphasized anxiety in different cardiac populations, including patients with myocardial infarction, aortic valve stenosis, congenital heart disease, arrhythmias, and cardiac devices (Cook et al., 2023; Martínez, 2023; Sandhu et al., 2021; Särnholm et al., 2025). Anxiety has also been linked with emotional dysregulation and self-care difficulties in cardiovascular contexts, supporting the present finding that psychological variables contribute independently to quality of life risk (Giacomo et al., 2023). The importance of anxiety is further supported by research on patients with CRT devices and cardiac arrhythmias, where distress may persist even in the absence of acute shock therapy or immediate life-threatening events (Florou et al., 2025; Willy et al., 2024). Together, these findings suggest that anxiety should be treated as a core quality-of-life determinant rather than a secondary emotional reaction.

Behavioral variables also played an important role in the model. Lower self-care maintenance and lower physical activity were associated with higher predicted risk of poor quality of life. These results indicate that quality of life is strongly connected to what patients are able to do in daily life, not only to what is recorded in their clinical chart. Poor self-care may increase symptom instability, delay treatment-seeking, reduce adherence, and contribute to repeated deterioration. Low physical activity may worsen deconditioning, fatigue, perceived disability, and social withdrawal. Prior work has supported the relevance of physical exercise and rehabilitation for quality of life in cardiac disease (Wungouw, 2021). Cardiovascular rehabilitation has also been associated with psychophysiological changes, suggesting that structured behavioral intervention may influence both physical and emotional functioning (Wagner-Skacel et al., 2021). Mind–body approaches and environmental interventions, including forest therapy, further support the broader idea that behavioral activation, stress regulation, and embodied intervention may improve well-being in chronic disease contexts (Suksatan & Tankumpuan, 2021; Yi et al., 2022).

Perceived stress and perceived social support were also among the top predictors, although their relative contributions were smaller than depression, functional class, and sleep quality. Higher perceived stress increased the likelihood of poor quality of life, while stronger perceived social support reduced it. This pattern is consistent with research showing that coping, emotional regulation, and social context influence psychological distress among individuals with cardiac disease (Sowan et al., 2026). It also aligns with the broader psycho-cardiology literature emphasizing that patients' adaptation to cardiac disease depends partly on coping resources, interpersonal support, and access to psychologically informed care (Sall et al., 2022; Smolderen et al., 2024). The relevance of stress and social support may also be interpreted in light of chronic illness vulnerability more broadly, where medically compromised patients often experience psychological strain that affects treatment experience and health-related functioning (Abiko et al., 2021). These findings reinforce the need to assess not only symptoms of depression and anxiety but also the patient's coping environment, perceived burden, and available support systems.

5. Conclusion

The results support the emerging view that cardiovascular and psychological mechanisms are reciprocally connected. The predictive importance of depression, anxiety, sleep, stress, self-care, and social support suggests that poor quality of life in heart failure is not reducible to cardiac pump function or hospitalization history. Instead, poor quality of life appears to reflect a clinical state in which physiological vulnerability, emotional distress, behavioral limitation, and social depletion converge. This interpretation is consistent with newer psycho-cardiologic perspectives exploring shared biological pathways, including gut microbiome mechanisms and cardiovascular therapeutics relevant to anxiety treatment (Fang et al., 2025; Repova et al., 2022). It is also consistent with evidence from related chronic and cardiovascular populations showing that cognitive impairment, psychopathology, psychosocial resources, and physical limitations can jointly shape health-related functioning (Moran et al., 2021; Tizzoni et al., 2025; Wagner et al., 2020). Therefore, the main contribution of the present study is not only that LightGBM predicted poor quality of life with good accuracy, but also that the interpretable model clarified the multidomain structure of quality-of-life risk in heart failure.

6. Limitations & Suggestions

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design limits causal inference, and the results should be interpreted as predictive associations rather than evidence that the identified variables directly caused poor quality of life. Second, although the sample was recruited from multiple Swedish heart failure clinics, the findings may not be fully generalizable to patients in rural settings, patients with acute decompensated heart failure, institutionalized patients, or individuals with severe cognitive impairment who were unable to complete self-report measures. Third, several behavioral and psychological variables were measured through self-report questionnaires, which may be affected by recall bias, social desirability, mood state, and differences in health literacy. Fourth, the model was internally tested using a held-out subset, but external validation in an independent sample was not performed. Finally, although SHAP analysis improved interpretability, machine learning explanations remain model-dependent and should be interpreted as indicators of predictive contribution rather than definitive causal mechanisms.

Future research should validate the proposed LightGBM model in larger and more diverse heart failure populations, including patients from different healthcare systems, socioeconomic backgrounds, and clinical settings. Longitudinal studies are particularly needed to determine whether the identified predictors can forecast future deterioration or improvement in quality of life over time. Future models should also incorporate additional information such as biomarkers, medication adherence records, wearable-device physical activity data, sleep-monitoring data, hospitalization trajectories, frailty measures, and healthcare utilization patterns. Comparative studies should evaluate LightGBM against other machine learning algorithms and conventional regression models to determine whether the added complexity of machine learning provides meaningful clinical benefit. Future research should also examine whether risk prediction can be linked to targeted interventions, such as psychological support, sleep treatment, rehabilitation referral, self-care education, or social support enhancement, and whether such model-guided care improves patient-reported outcomes.

The findings suggest that routine heart failure care should include systematic assessment of quality of life together with psychological, behavioral, and sleep-related indicators. Clinicians should pay particular attention to patients with elevated depressive symptoms, advanced functional limitation, poor sleep quality, anxiety symptoms, recent hospitalization, weak self-care, low physical activity, high perceived stress, and limited social support. A machine learning-based risk prediction tool could be used as a screening aid to identify patients who may benefit from more comprehensive evaluation and multidisciplinary support. In practice, patients identified as being at high risk for poor quality of life should receive coordinated care that includes medical optimization, self-care counseling, physical activity or rehabilitation planning, sleep assessment, psychological screening, and referral to mental health or psychosocial services when needed. The model should not replace clinical judgment, but it can strengthen patient-centered decision-making by helping care teams recognize complex risk patterns that may otherwise remain unnoticed during routine clinical visits.

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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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