Survival Analysis of Heart Failure Patients Using the Cox Proportional Hazards Model

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Abstrak. *Penelitian ini menerapkan model Cox Proportional Hazards untuk menganalisis ketahanan hidup pasien gagal jantung menggunakan dataset Heart Failure Clinical Records. Analisis Kaplan–Meier digunakan untuk mengestimasi probabilitas ketahanan hidup, regresi Cox digunakan untuk mengidentifikasi faktor risiko klinis yang signifikan. Model full-cohort menghasilkan apparent Concordance Index sebesar 0,7408, evaluasi pada held-out test set dari stratified 75:25 train–test split menghasilkan mean time-dependent AUC sebesar 0,7506 dan Integrated Brier Score sebesar 0,1658. Usia, serum creatinine, hipertensi, anemia, creatinine phosphokinase, dan ejection fraction menjadi prediktor signifikan terhadap mortalitas. Hasil penelitian menunjukkan bahwa analisis survival memberikan informasi prognosis yang lebih komprehensif dibandingkan klasifikasi biner karena mampu mengestimasi risiko kematian dan probabilitas ketahanan hidup. Pendekatan ini juga dapat mendukung stratifikasi risiko pasien serta pengambilan keputusan klinis yang lebih terarah. Pendekatan ini memberikan kerangka yang dapat diinterpretasikan untuk profil risiko dan estimasi survival individual, tetapi memerlukan validasi eksternal sebelum digunakan untuk mendukung keputusan klinis.*
Kata Kunci: *Gagal Jantung, Analisis Survival, Cox Proportional Hazards, Kaplan–Meier, Prediksi Ketahanan Hidup*

Abstract. *This study applies the Cox Proportional Hazards model to analyze survival outcomes in heart failure patients using the Heart Failure Clinical Records dataset. Kaplan–Meier analysis used to estimate survival probabilities, Cox regression employed to identify significant clinical risk factors. The fitted full-cohort model yielded apparent Concordance Index of 0.7408, whereas held-out test evaluation from stratified 75:25 train–test split yielded a mean time-dependent AUC of 0.7506 and Integrated Brier Score of 0.1658. Age, serum creatinine, high blood pressure, anaemia, creatinine phosphokinase, and ejection fraction were identified as significant predictors of mortality. The results indicate that survival analysis provides more comprehensive prognostic information than binary classification because it estimates both mortality risk and patient survival probability. This approach also support patient risk stratification and facilitate more targeted clinical decision-making. This approach provides interpretable framework for patient risk profiling and individualized survival estimation, but external validation is required before clinical use.*
Keywords: *Heart Failure, Survival Analysis, Cox Proportional Hazards, Kaplan–Meier, Survival Prediction*

1. Introduction

As a major contributor to global morbidity and mortality, heart failure (HF) affects millions of people and places considerable pressure on healthcare systems worldwide. [1] Despite continuous advances in medical diagnosis and treatment, patients with heart failure remain at high risk of hospitalization, disease progression, and premature death. The complex interactions among demographic characteristics, comorbidities, and clinical biomarkers make prognosis highly challenging. [2] Accordingly, reliable evaluation of patient prognosis is crucial for supporting individualized treatment strategies and informed clinical decision-making.

Early identification of high-risk heart failure patients enables clinicians to initiate timely interventions, optimize therapeutic strategies, and allocate healthcare resources more effectively. Reliable prognostic models can assist physicians in distinguishing patients who require intensive monitoring from those with relatively favorable outcomes. [3] The growing availability of electronic health records and clinical datasets has encouraged the extensive application of machine learning and statistical modeling approaches to enhance mortality risk prediction and facilitate evidence-based clinical practice. [4]

This study employs a survival analysis framework based on the Cox Proportional Hazards model to estimate the prognosis of patients with heart failure using the Heart Failure Clinical Records dataset. Unlike conventional approaches that primarily focus on binary mortality classification, the proposed framework incorporates both event occurrence and follow-up time, enabling a more comprehensive assessment of patient outcomes. Specifically, the study identifies significant clinical factors associated with mortality through hazard ratio estimation, estimates patient-specific survival probabilities across different follow-up periods, and stratifies patients into clinically interpretable risk groups based on predicted hazard scores. By integrating these components, the proposed approach provides a more informative representation of disease prognosis and supports personalized risk assessment and clinical decision-making in heart failure management. The methodological contribution is not the introduction of Cox regression itself, but the integration of multivariable hazard estimation, time-dependent discrimination, prediction-error assessment, and patient-specific survival trajectories within a single analysis framework. Accordingly, the framework is intended for exploratory prognostic assessment rather than direct clinical decision-making.

2. Literature Review

Heart failure prognosis has been extensively examined using established machine learning methods, such as Logistic Regression, Random Forest, Support Vector Machine, XGBoost, and LightGBM, as well as a range of deep learning architectures. [5] Within health informatics, identifying clinically relevant variables is essential for enhancing predictive performance while limiting model complexity, as demonstrated by prior research on feature selection in multi-disease classification. [6] Similar observations have also been reported in biomedical signal processing studies, where appropriate feature extraction and preprocessing substantially improved the robustness of machine learning models. [7] These approaches have demonstrated promising predictive performance by classifying patients into binary outcomes, namely survival or death. Their primary objective is to maximize classification accuracy through the identification of discriminative clinical features associated with mortality. While these models provide valuable prognostic information, they generally formulate the problem as a static binary classification task. [8]

Although binary classification models have achieved encouraging predictive performance, they overlook an important aspect of clinical prognosis: the timing of the event. Patients who die shortly after diagnosis and those who survive for several months before death receive the same class label despite having substantially different clinical trajectories. [9] Furthermore, conventional classification methods cannot adequately accommodate censored observations, in which patients remain alive at the end of the follow-up period. Consequently, these approaches fail to capture the temporal dynamics of disease progression and survival outcomes. [10]

Time-to-event outcomes are more appropriately examined through survival analysis because this framework incorporates both whether an event occurs and the length of the observation period. A widely employed method within this field is the Cox Proportional Hazards (Cox PH) model, a semi-parametric technique that supports hazard ratio estimation and accommodates censored data without specifying the underlying baseline hazard function. [11] Unlike binary classification methods, the Cox PH model quantifies the relative effect of clinical variables on the instantaneous risk of mortality and enables estimation of patient survival probabilities over time. These characteristics make survival analysis particularly suitable for supporting longitudinal prognosis and clinical risk assessment in heart failure patients. [12]

The most directly comparable baseline is Ahmad et al. [13], who analyzed the same 299-patient heart-failure cohort using Kaplan–Meier analysis and Cox regression, with 200 bootstrap replications, a calibration slope, and ROC-based discrimination. In contrast, the present study keeps continuous predictors on their continuous scale and complements the Cox model with time-dependent AUC, Integrated Brier Score, and illustrative patient-specific survival trajectories. Because the variable representations and validation procedures differ, the numerical performance values are not directly comparable.

3. Methods

The methodological procedures employed in this research are outlined in this section, including the dataset description, preprocessing stages, Kaplan–Meier survival estimation, Cox proportional hazards analysis, and the performance metrics applied to evaluate the predictive capability of the proposed model.

3.1. Dataset Description

The analysis was conducted using the publicly accessible Heart Failure Clinical Records dataset, originally derived from 299 heart-failure patients admitted to Faisalabad Institute of Cardiology and Allied Hospital in Faisalabad, Pakistan, during April–December 2015. The source cohort included patients aged 40 years or older with left ventricular systolic dysfunction and New York Heart Association (NYHA) class III or IV heart failure; the public source does not document additional exclusion criteria beyond this cohort definition [13]. Follow-up ranged from 4 to 285 days. Of the 299 patients, 96 experienced death during follow-up and 203 were right-censored.

Table 1. Dataset Characteristics

Variable	Unit / coding	Mean ± SD or n (%)	Median [IQR]	Range
Age	years	60.83 ± 11.89	60.00 [51.00–70.00]	40.00–95.00
Creatinine phosphokinase	mcg/L	581.84 ± 970.29	250.00 [116.50–582.00]	23.00–7861.00
Ejection fraction	%	38.08 ± 11.83	38.00 [30.00–45.00]	14.00–80.00
Platelets	kiloplatelets/mL	263358.03 ± 97804.24	262000.00 [212500.00–303500.00]	25100.00–850000.00
Serum creatinine	mg/dL	1.39 ± 1.03	1.10 [0.90–1.40]	0.50–9.40
Serum sodium	mEq/L	136.63 ± 4.41	137.00 [134.00–140.00]	113.00–148.00
Follow-up time	days	130.26 ± 77.61	115.00 [73.00–203.00]	4.00–285.00
Anaemia	0 = no, 1 = yes	129 (43.1%)	-	0–1
Diabetes	0 = no, 1 = yes	125 (41.8%)	-	0–1
High blood pressure	0 = no, 1 = yes	105 (35.1%)	-	0–1
Sex	binary coding in source dataset	194 (64.9%)	-	0–1
Smoking	0 = no, 1 = yes	96 (32.1%)	-	0–1
Death event	0 = censored, 1 = death	96 (32.1%)	-	0–1

The analysis was conducted using the publicly accessible Heart Failure Clinical Records dataset, comprising clinical data from 299 patients diagnosed with heart failure. A total of 13 variables are included, covering demographic attributes, laboratory findings, comorbid conditions, follow-up time, and mortality status. Follow-up duration is recorded in days through the variable time, while DEATH_EVENT denotes the observed outcome: a value of 1 indicates that the patient died during follow-up, whereas 0 represents a censored observation. A complete description of the dataset variables is provided in Table 1.

The availability of both time-to-event information and event status makes this dataset appropriate for survival analysis. The variable time records the duration of patient follow-up in days, while DEATH_EVENT identifies the outcome observed during this period. A value of 1 denotes that death occurred, whereas a value of 0 indicates that the patient was alive at the last recorded follow-up and was therefore treated as a censored observation.

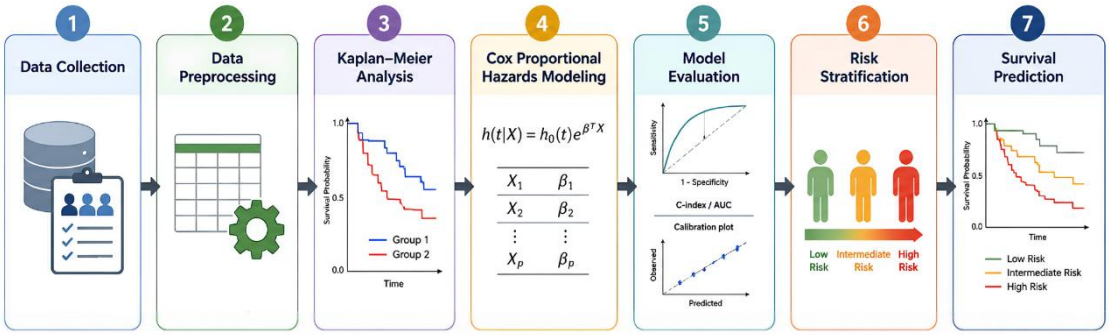


Figure 1. Workflow of the proposed survival analysis framework

3.2. Data Preprocessing

The dataset underwent an initial quality assessment before survival analysis. The assessment covered missing values, duplicate observations, non-positive follow-up times, invalid event coding, and consistency across variable types. No missing values, duplicate rows, non-positive follow-up times, or invalid event codes were identified; therefore, no observations were removed and the final analytical sample remained 299 patients. Continuous variables were retained on their original scale, while dichotomous variables were coded as 0 or 1.

Patients with DEATH_EVENT = 0 were treated as right-censored observations during model development. Multicollinearity among the 11 predictors was assessed using the Variance Inflation Factor (VIF). All VIF values were low (1.029–1.338), indicating no concerning multicollinearity. The Cox model was fitted with a small L2 penalizer of 0.01, consistent with the analytical implementation. The overall preprocessing and modeling workflow is illustrated in Figure 1.

3.3. Kaplan–Meier Estimator

Survival probabilities throughout the observation period were derived using the Kaplan–Meier estimator. This non-parametric approach constructs the survival function by incorporating incomplete follow-up information from right-censored patients. [14] The estimated survival function is expressed in Equation (1).

$$\hat{S}(t) = \prod_{t_i \le t} \left(1 - \frac{d_i}{n_i}\right) \tag{1}$$

In this formulation, $\hat{S}(t)$ represents the estimated probability of survival up to time t, The term t_i denotes the time at which an event was observed, d_i corresponds to the number of events recorded at t_i, and n_i indicates the number of patients who remained at risk immediately before t_i. The Kaplan–Meier estimator

was subsequently applied to illustrate the overall survival pattern among patients with heart failure and to examine differences in survival outcomes across the predicted risk categories.

3.4. Cox Proportional Hazards Model

The Cox Proportional Hazards (Cox PH) model was applied to determine which clinical variables were associated with mortality risk. Hazard estimation was performed by simultaneously incorporating follow-up time and event status, while appropriately accommodating right-censored observations. [15] The hazard function of the Cox PH model is expressed in Equation (2).

$$h(t|\mathrm{x}) = h_0(t)\exp(\beta^T \mathrm{x}) \tag{2}$$

where $h(t|\mathrm{x})$ denotes the hazard function at time t, $h_0(t)$ is the baseline hazard function, x represents the vector of clinical covariates, and β^T denotes the corresponding regression coefficient vector. The effect of each predictor variable was quantified using the hazard ratio (HR), as defined in Equation (3).

$$HR = \exp(\beta) \tag{3}$$

where HR denotes the hazard ratio and β represents the estimated regression coefficient of a predictor variable. An (HR > 1) indicates an increased mortality risk, whereas an (HR < 1) indicates a reduced mortality risk. Variables with ($p < 0.05$) were considered statistically significant. The proportional hazards assumption was formally assessed using Schoenfeld-residual diagnostics with a significance threshold of 0.05.

3.5. Model Evaluation

The performance of the proposed Cox proportional hazards model was examined in terms of discriminative ability, separation of survival distributions, and prediction error. Discrimination was quantified using the Concordance Index (C-index), while differences in survival between the predicted risk groups were examined through the Log-rank test. Time-varying predictive accuracy was additionally measured using the time-dependent Area Under the Receiver Operating Characteristic Curve (AUC) and the Integrated Brier Score (IBS). [16] The Concordance Index (C-index) was applied to measure the model's ability to accurately rank patients based on their predicted mortality risk. The C-index is formulated as shown in Equation (4). The C-index reported for the fitted full-cohort Cox model is interpreted as an apparent discrimination estimate. For the time-dependent evaluation, the analysis notebook used a stratified 75:25 train–test split (random_state = 42). Time-dependent AUC was evaluated at 30, 60, 90, 120, 180, and 240 days, while the IBS summarized prediction error over the common follow-up interval. Right-censoring was handled using the inverse-probability-of-censoring weighting procedure implemented in scikit-survival. These measures represent different evaluation views and are not treated as directly interchangeable.

$$C = \frac{\sum_{i<j} I\left(r_i > r_j\right)\delta_{ij}}{\sum_{i<j} \delta_{ij}} \tag{4}$$

where N denotes the total number of comparable patient pairs, $I(\cdot)$ is the indicator function, r_i and r_j denote the predicted risk scores, and δ_{ij} indicates whether the patient pair is comparable.

The Log-rank test was applied to compare the survival distributions of two model-derived risk groups. Predicted risk was defined by the partial-hazard score from the fitted full-cohort Cox model. Patients with scores above the cohort median (0.9630) were assigned to the high-risk group (n = 149), whereas those with scores at or below the median were assigned to the low-risk group (n = 150). The corresponding Log-rank test statistic is expressed in Equation (5). This median split was used only to assess survival-curve separation and was not intended as a validated clinical cutoff. Separately, the three patient-level profiles presented in Section 4.4 were selected from the fitted partial-hazard scores as the

highest-risk case, the case nearest the median score, and the lowest-risk case. These profiles are illustrative and are not proposed as validated clinical cutoffs.

$$\chi^2 = \frac{(O - E)^2}{V} \tag{5}$$

where O denotes the observed number of events, E is the expected number of events under the null hypothesis, and V represents the variance of $O - E$.

The model's discriminative ability across different follow-up periods was assessed using the time-dependent Area Under the Receiver Operating Characteristic Curve (AUC), which accounts for right-censored observations. [17] The time-dependent AUC is calculated as shown in Equation (6).

$$AUC(t) = P\left(R_i > R_j \mid T_i \leq t,\ T_j > t\right) \tag{6}$$

where R_i and R_j denote the predicted risk scores of patients i and j, respectively, and T represents the observed survival time. Higher AUC values indicate better discrimination between high-risk and low-risk patients at a given follow-up time.

The overall prediction error of the survival model across the complete follow-up period was measured using the Integrated Brier Score (IBS). The IBS is defined as shown in Equation (7).

$$IBS = \frac{1}{\tau}\int_0^{\tau} B\,S(t)\,dt \tag{7}$$

where $BS(t)$ represents the Brier score evaluated at time t, while τ denotes the maximum follow-up duration. A lower IBS value reflects closer agreement between the predicted survival probabilities and the observed patient outcomes.

4. Results and Discussion

This section presents the experimental results of the proposed Cox proportional hazards model. The analysis includes descriptive statistics of the patient cohort, survival estimation using the Kaplan–Meier estimator, identification of significant clinical risk factors through Cox regression, risk stratification, and model performance evaluation using multiple survival analysis metrics.

4.1. Kaplan–Meier Survival Analysis

The Kaplan–Meier estimator was applied to estimate the overall survival probability of heart failure patients throughout the follow-up period. The resulting survival curve is presented in Figure 2, while the estimated survival probabilities at selected follow-up times are summarized in Table 2.

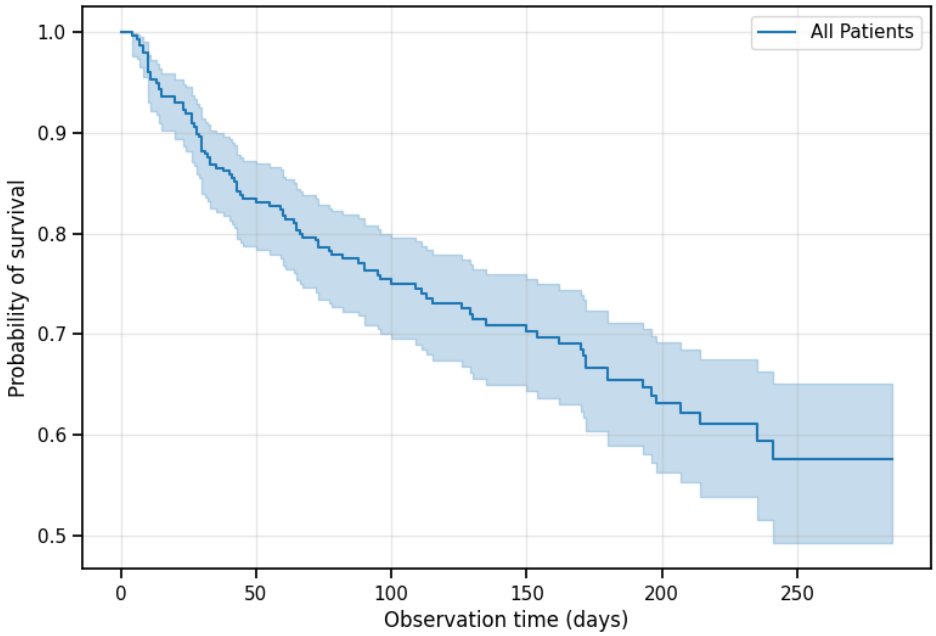


Figure 2. Kaplan–Meier Curve of All Patients

Figure 2 demonstrates a gradual decline in the estimated survival probability as deaths accumulated during follow-up. This pattern describes the cohort's survival experience but does not, by itself, establish that the instantaneous mortality hazard increased over time. As shown in Table 2, the estimated survival probability was 88.23% at 30 days, decreasing to 76.27% at 90 days, 65.43% at 180 days, and 57.57% at 270 days. The widening confidence intervals toward the end of follow-up reflect the decreasing number of patients remaining at risk and the resulting greater uncertainty in the survival estimates. The model-derived high-risk group experienced 79 deaths among 149 patients, compared with 17 deaths among 150 patients in the low-risk group. The Log-rank test showed a significant difference between their survival distributions (χ^2 = 55.826, $p < 0.001$). Overall, the Kaplan–Meier analysis describes the temporal survival pattern of the study cohort and supports the observed separation between the model-derived risk groups.

Table 2. Estimated Survival Probabilities

Follow-up Time (days)	Survival Probability
30	0.8823
90	0.7627
180	0.6543
270	0.5757

4.2. Clinical Risk Factors Identified by the Cox Model

Statistically significant relationships with mortality were observed for six clinical factors in the Cox proportional hazards model ($p < 0.05$). These factors comprised age, anaemia, creatinine phosphokinase, ejection fraction, high blood pressure, and serum creatinine. Table 3 reports the estimated hazard ratios with their 95% confidence intervals, while Figure 3 provides a graphical representation of these results. Serum creatinine was positively associated with mortality hazard (HR = 1.371 per 1 mg/dL), whereas ejection fraction was inversely associated with the hazard of death. Because the continuous predictors use different units and scales, their hazard-ratio magnitudes were not compared to designate a single strongest factor. The multicollinearity assessment showed a maximum VIF of 1.338. Schoenfeld-residual diagnostics indicated a violation of the proportional-hazards assumption for ejection fraction ($p = 0.0171$), whereas the remaining predictors did not cross the 0.05 threshold. Consequently, the ejection-

fraction coefficient should be interpreted as an average association over the observed follow-up period.

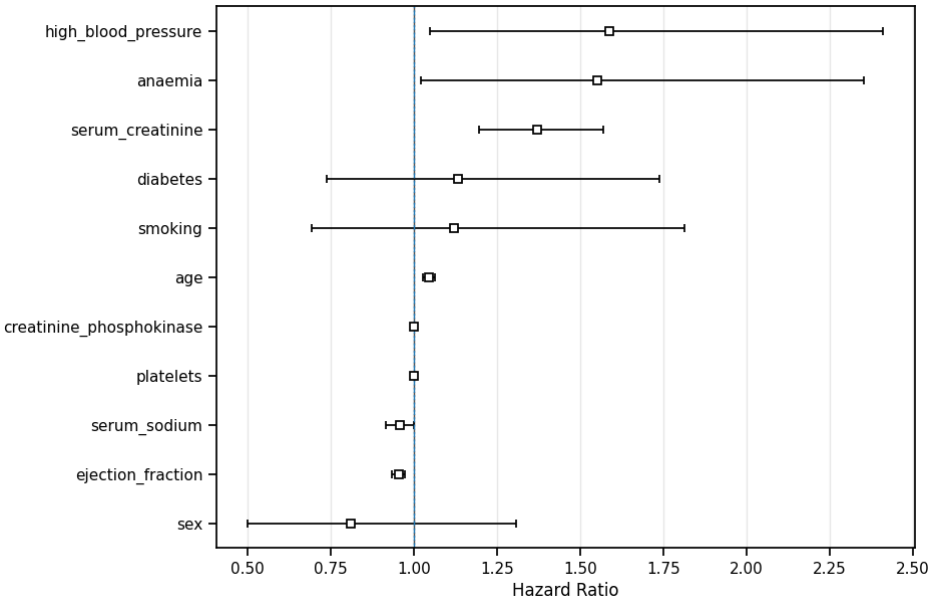


Figure 3. Forest plot of hazard ratios with 95% confidence intervals.

Table 3. Cox Proportional Hazards Regression Results

Variable	β	HR	95% CI	p-value
Age	0.0445	1.0455	1.0270–1.0644	<0.001
Anaemia	0.4395	1.5520	1.0231–2.3542	0.039
Creatinine Phosphokinase	0.0002	1.0002	1.0000–1.0004	0.033
Diabetes	0.1245	1.1326	0.7383–1.7374	0.568
Ejection Fraction	-0.0466	0.9545	0.9357–0.9737	<0.001
High Blood Pressure	0.4634	1.5895	1.0477–2.4114	0.029
Platelets	-0.0000	1.0000	1.0000–1.0000	0.711
Serum Creatinine	0.3156	1.3710	1.1963–1.5713	<0.001
Serum Sodium	-0.0438	0.9572	0.9153–1.0010	0.055
Sex	-0.2108	0.8100	0.5015–1.3082	0.389
Smoking	0.1151	1.1220	0.6944–1.8129	0.638

Age, high blood pressure, anaemia, serum creatinine, and creatinine phosphokinase were positively associated with mortality risk. Age showed a hazard ratio (HR) of 1.046 ($p < 0.001$), indicating that each additional year of age increased the hazard of death by approximately 4.6%. Patients with high blood pressure and anaemia exhibited 59.0% and 55.2% higher mortality hazards than those without these conditions, respectively. Serum creatinine was also significantly associated with mortality hazard (HR = 1.371 per 1 mg/dL, $p < 0.001$); however, this HR magnitude should not be used to label it as the strongest factor because continuous predictors are expressed in different measurement units and scales. Creatinine phosphokinase was statistically significant (HR = 1.0002 per 1 mcg/L, $p = 0.033$). Although the per-unit HR is close to 1, a 100 mcg/L increase corresponds to an HR of approximately 1.021. Its clinical relevance should therefore be interpreted over a meaningful change in CPK and in the context of the observed value range, rather than from the one-unit HR alone.

4.3. Cox Proportional Hazards Regression

Table 4 summarizes metrics obtained from two evaluation settings, whereas Figure 4 presents discrimination on the held-out test set at multiple follow-up time points. The fitted full-

cohort model produced an apparent Concordance Index (C-index) of 0.7408, indicating moderate ranking ability within the analyzed cohort rather than independent test performance. Its partial log-likelihood was −469.6065 and its partial Akaike Information Criterion (AIC) was 961.2130. By contrast, the mean time-dependent AUC and IBS were calculated on the held-out test set from the stratified 75:25 train–test split.

Table 4. Performance Evaluation of the Proposed Cox Proportional Hazards Model

Metric	Value
Concordance Index (C-index)	0.7408
Partial Log-Likelihood	−469.6065
Partial AIC	961.2130
Mean Time-dependent AUC	0.7506
Integrated Brier Score (IBS)	0.1658

As shown in Figure 4, the time-dependent AUC varied across the follow-up period, with a noticeable decline around 90 days followed by partial recovery at later evaluation points. The performance metrics reported in this study were obtained from two different evaluation settings. The C-index of 0.7408, partial log-likelihood of −469.6065, and partial AIC of 961.2130 are apparent estimates obtained from the fitted full-cohort model. In contrast, the mean time-dependent AUC of 0.7506 and Integrated Brier Score (IBS) of 0.1658 are held-out test estimates obtained from the stratified 75:25 train–test split. The mean time-dependent AUC indicates useful discrimination while accounting for right-censored observations, whereas the IBS summarizes the overall survival-prediction error across the evaluated follow-up period. However, because the IBS alone does not establish calibration quality, these results should not be interpreted as evidence that the model is well calibrated without a dedicated calibration analysis.

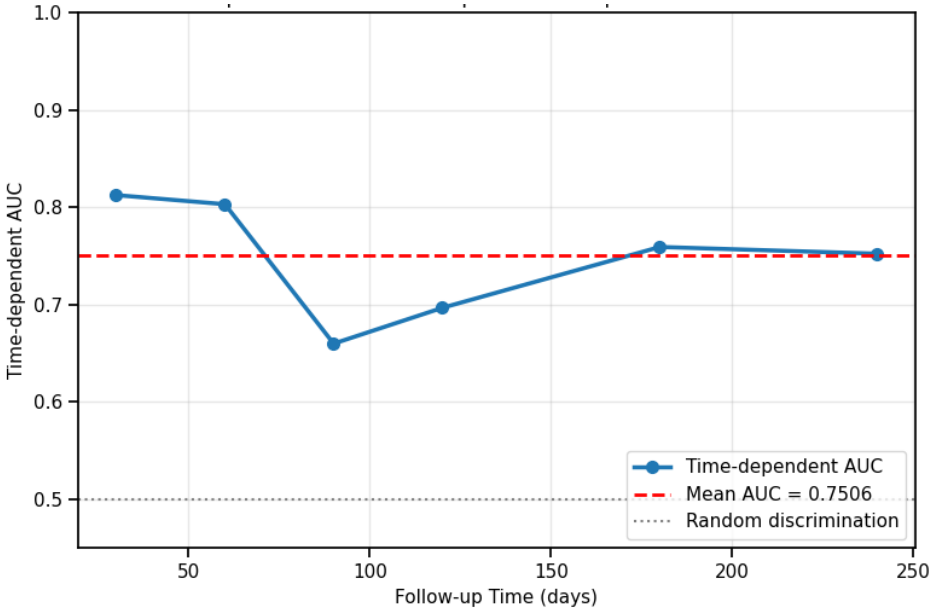


Figure 4. Time-dependent AUC of Proposed Cox Proportional Hazards Model

4.4. Discussion

The fitted Cox proportional hazards model was used to estimate patient-specific survival functions for three representative risk profiles. Patient A was the patient with the highest predicted partial-hazard score, Patient B was the patient whose score was nearest the cohort median, and Patient C was the patient with the lowest predicted score. Their clinical characteristics and predicted risk scores are presented in Table 5, while the corresponding survival probabilities at selected follow-up times are summarized in Table 6. The resulting individual survival curves are illustrated in Figure 5.

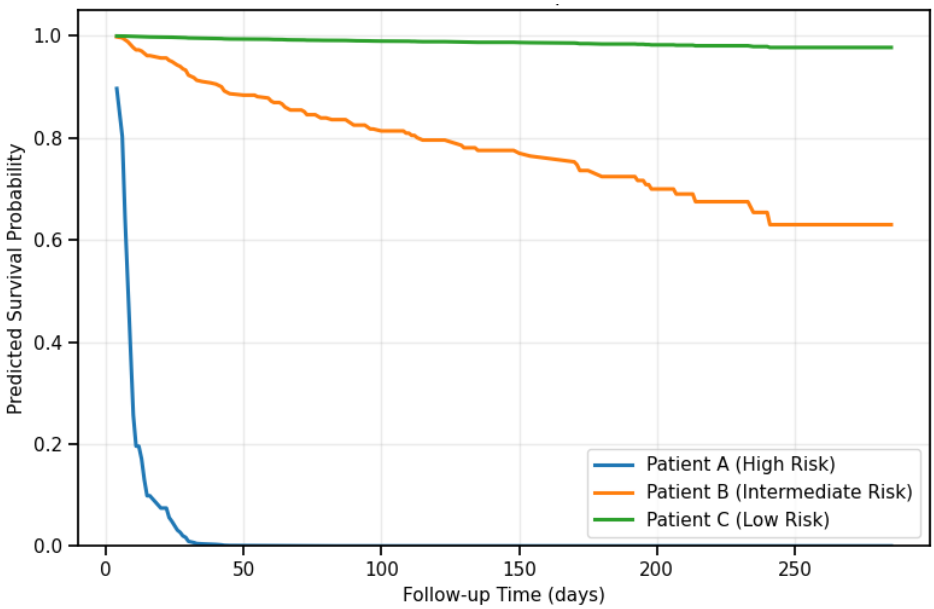


Figure 5. Predicted survival curves for representative heart failure patients

The predicted survival functions showed substantial differences across the three representative risk profiles. Patient A had the highest predicted risk score of 56.6673 and exhibited a sharply declining survival probability. The estimated probability of surviving beyond 30 days was only 0.91% and approached zero at later follow-up times. This unfavorable prognosis was associated with advanced age, anaemia, high blood pressure, elevated serum creatinine, smoking status, and a relatively low ejection fraction.

Patient B demonstrated an intermediate survival pattern, with estimated survival probabilities of 92.32%, 82.52%, 72.42%, and 63.00% at 30, 90, 180, and 270 days, respectively. Although Patient B had a low serum creatinine level and no anaemia or high blood pressure, the low ejection fraction of 25% contributed to an intermediate predicted risk profile. In contrast, Patient C maintained the highest survival probabilities across the follow-up period, remaining above 97% at 270 days. This favorable prediction was primarily associated with younger age, the absence of major comorbidities, and a high ejection fraction of 80%.

These patient-specific predictions demonstrate the ability of the Cox proportional hazards model to represent heterogeneous survival trajectories that cannot be captured by conventional binary mortality classification. Instead of assigning only a death or survival label, the model provides time-dependent survival estimates based on each patient's clinical profile. Nevertheless, the predictions represent model-based estimates derived from a limited dataset and should not be interpreted as direct clinical recommendations.

Table 5. Clinical Characteristics and Predicted Risk Scores of Representative Patients

Variable	Patient A High Risk	Patient B Intermediate Risk	Patient C Low Risk
Age (years)	80	55	45
Anaemia	1	0	0
Creatinine Phosphokinase	123	2017	582
Diabetes	0	0	0
Ejection Fraction (%)	35	25	80
High Blood Pressure	1	0	0
Platelets	388,000.00	314,000.00	263,358.03
Serum Creatinine (mg/dL)	9.40	1.10	1.18
Serum Sodium (mEq/L)	133	138	137
Sex	1	1	0
Smoking	1	0	0
Predicted Risk Score	56.6673	0.9630	0.0476

Table 6. Predicted Survival Probabilities of Representative Patients

Patient	30 Days	90 Days	180 Days	270 Days
Patient A High Risk	0.0091	<0.0001	<0.0001	<0.0001
Patient B Intermediate Risk	0.9232	0.8252	0.7242	0.6300
Patient C Low Risk	0.9961	0.9905	0.9842	0.9774

Furthermore, these representative cases illustrate how survival analysis supports individualized risk stratification by providing continuous survival probabilities over time rather than a single binary prediction. The profiles are descriptive model-based examples rather than validated clinical risk categories. The study is based on a small public cohort from two hospitals in one city, and no independent external cohort was available. Accordingly, the findings require validation in larger, independent, and preferably multicenter cohorts before practical clinical implementation.

5. Conclusion and Suggestions

A Cox Proportional Hazards-based survival analysis framework was developed to predict the prognosis of patients with heart failure using the Heart Failure Clinical Records dataset. In contrast to standard binary classification methods, this framework incorporates both event status and observation time, allowing mortality risk and individualized survival probabilities to be estimated simultaneously. The fitted full-cohort model yielded an apparent C-index of 0.7408, while the time-dependent evaluation reported a mean AUC of 0.7506 and an Integrated Brier Score of 0.1658. Six clinical variables—age, serum creatinine, high blood pressure, anaemia, creatinine phosphokinase, and ejection fraction—were identified as statistically significant predictors of mortality, although the proportional-hazards assumption for ejection fraction was not fully satisfied. Overall, the framework provides interpretable exploratory survival estimates and patient-level risk profiles. External validation using larger and preferably multicenter cohorts is required before the model can be considered for clinical decision support. Further research should also benchmark Cox-based models against contemporary machine-learning and deep-learning survival techniques.

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