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Development Of A Clinical Prediction Model For In-Hospital Mortality Among Patients With Heart Failure: A Tertiary Care Hospital Study

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Abstract

Heart failure (HF) now represents a major and growing global public health challenge, affecting an estimated 26 million individuals worldwide, with prevalence that is continuing to rise due to population ageing and improved survival from cardiovascular diseases (Savarese & Lund, 2017). In the United States alone, approximately 5.7 million people are currently living with HF, and this number is projected to exceed 8 million by 2030, reflecting a nearly 46% increase in prevalence (Bozkurt et al., 2023, Gola MSG et al 2024). Cardiovascular diseases, including myocardial infarction and stroke, remain leading contributors to HF burden, with approximately 805,000 myocardial infarctions occurring annually in the United States (Virani et al., 2020).

The burden is even more concerning in low- and middle-income countries, particularly in India, where cardiovascular mortality rates are disproportionately high. India accounts for nearly one-fifth of global deaths due to ischemic heart disease and stroke (World Health Organization [WHO], 2021). Notably, cardiovascular events in India occur at younger ages compared to Western populations, with nearly 50% of myocardial infarctions occurring in individuals under 50 years of age (Arora et al 2019, Zeitouni 2020). Mortality rates following HF diagnosis in India are also significantly higher, reflecting gaps in early detection, risk stratification, and long-term disease management.

Introduction

Clinically, HF is a complex syndrome characterized by structural or functional cardiac abnormalities that impair the heart's ability to pump or fill effectively, leading to inadequate tissue perfusion and/or congestion (Heidenreich et al., 2022). Contemporary clinical frameworks classify HF across a continuum, from individuals at risk (Stage A), to preclinical disease (Stage B), symptomatic HF (Stage C), and advanced or refractory HF (Stage D), requiring specialized interventions such as mechanical circulatory support or transplantation (Heidenreich et al., 2022). Despite advances in pharmacological and device-based therapies, HF remains associated with high rates of hospitalization, morbidity, and mortality.

Patients with advanced HF frequently require intensive care unit (ICU) admission due to acute de-compensation and multi-organ dysfunction, necessitating high-resource, multidisciplinary care. While significant progress has been made in identifying prognostic indicators through clinical trials, these findings often lack generalizability to real-world populations, particularly in diverse community and resource-limited settings (Ambrosy et al., 2014). Consequently, there remains a critical need for robust, context-specific tools to accurately predict outcomes such as mortality and re-hospitalization.

Predictive modelling has emerged as a promising approach to address this gap. By leveraging statistical methods and machine learning algorithms—including logistic regression, decision trees, random forests, and neural networks—predictive models can analyze complex interactions among demographic, clinical, and laboratory variables to forecast patient outcomes (Shipe et al., 2019). These models typically involve systematic processes such as data collection, pre-processing, feature selection, model development, and validation.(Hilton et al, 2020) Variables commonly incorporated include patient demographics, vital signs, comorbidities, laboratory parameters, and electrocardiographic findings.

Despite the growing interest in predictive analytics, existing HF mortality prediction models demonstrate only modest performance and limited clinical adoption (Yue Wey, 2025). Furthermore,

there is a relative scarcity of models developed using data from low- and middle-income countries, where disease patterns and healthcare access differ substantially (Mbanze et al, 2024).
Therefore, the present study aims to develop and validate a predictive model for mortality among patients with heart failure using routinely available hospital data. An accurate and clinically applicable prediction model could support early risk stratification, inform treatment decisions, optimize resource allocation, and ultimately reduce mortality, morbidity, and healthcare costs. By enhancing prognostic precision, such models may contribute to improved quality of life and better clinical outcomes for patients with heart failure.

Methodology
This study employed a retrospective observational design to develop and validate a predictive model for estimating the probability of mortality among patients diagnosed with heart failure (HF). The primary objective was to construct a risk equation quantifying the association between selected risk factors (independent variables) and mortality (dependent variable), thereby enabling individualized risk prediction.
Data were obtained from electronic health records (EHRs) of patients admitted with a diagnosis of HF to a tertiary care hospital located in Panchkula, Haryana, India. The dataset comprised routinely collected clinical information, including demographic characteristics, clinical parameters, and laboratory investigations recorded at the time of admission or during early hospitalization. Only variables readily available in standard clinical practice were considered to enhance the model's applicability.
Adult patients (aged ≥18 years) with a confirmed diagnosis of HF were included in the study. Patients were required to have complete documentation of key predictor variables and clearly defined clinical outcomes. Patients were excluded if they had missing or incomplete outcome data, substantial gaps in predictor variables, or duplicate or inconsistent records. These criteria ensured the reliability and internal validity of the dataset used for model development.
The primary outcome of interest was all-cause mortality. This was defined as a binary variable, coded as 1 for death and 0 for survival during the study period (in-hospital or defined follow-up duration). This binary classification enabled probabilistic modelling of mortality risk.
Selection of predictor variables was guided by prior literature and clinical relevance. Variables included: Demographic factors **(** age and gender), clinical variables (heart rate, systolic and diastolic blood pressure, left ventricular ejection fraction/ LVEF, ECG and obesity/BMI), Laboratory variables (hemoglobin, sodium, potassium, urea and creatinine levels), presence of co-morbidity (hypertension, diabetes, stroke, atrial arrhythmia, chronic obstructive pulmonary disease/COPD, anaemia) and Lifestyle factors **(**alcohol consumption and smoking status).Only variables available at baseline or early during hospitalization were included to facilitate real-time clinical application.

Results
A total of 173 patients with heart failure (HF) were enrolled in the study. After data cleaning and exclusion of records with critical missing or inconsistent values, 165 patients were included in the final analysis. The mean age of the study population was 66.8 ± 12.4 years, with a predominance of males (64.7%, n = 107). The overall in-hospital mortality rate was 17.6% (n = 29).

Baseline Characteristic
Patients who died during hospitalization were significantly older and demonstrated worse hemodynamic and biochemical profiles compared to survivors. Non-survivors had a higher heart rate , lower systolic blood pressure, reduced left ventricular ejection fraction (LVEF),higher serum creatinine, and lower sodium and hemoglobin levels

Table no.1: Baseline Characteristics

Variable	Survivors (n=136)	Non-survivors (n=29)	p-value
Age (years)	64.9 ± 11.8	73.2 ± 10.6	0.002
Male (%)	63%	69%	0.48

Variable	Survivors (n=136)	Non-survivors (n=29)	p-value
Heart Rate (bpm)	94 ± 22	108 ± 26	0.01
SBP (mmHg)	132 ± 28	108 ± 24	<0.001
LVEF (%)	38 ± 9	28 ± 7	<0.001
Creatinine (mg/dL)	1.4 ± 0.8	2.8 ± 1.6	<0.001
Sodium (mmol/L)	137 ± 5	130 ± 6	<0.001
Hemoglobin (g/dL)	12.4 ± 2.1	10.2 ± 1.8	0.003
Diabetes (%)	52%	72%	0.04
COPD (%)	12%	31%	0.01

Model Development

Data pre-processing included handling missing values, identifying outliers, and assessing variable distributions. Continuous variables were summarized using means and standard deviations or medians and interquartile ranges, while categorical variables were expressed as frequencies and percentages.

Univariable analyses were initially conducted to examine the association between each predictor and mortality. Variables demonstrating clinical relevance or statistical significance ($p < 0.05$) were included in the multivariable model.The performance of the predictive model was evaluated in terms of discrimination (assessed using the area under the receiver operating characteristic curve (AUC–ROC), with higher values indicating better ability to distinguish between survivors and non-survivors) and calibration(.evaluated using the Hosmer–Lemeshow goodness-of-fit test to assess agreement between observed and predicted outcomes). Internal validation was performed using either a split-sample approach (training and testing datasets) or k-fold cross-validation to assess model robustness and generalizability

The univariate logistic regression analysis identified the following variables to be significantly associated with mortality: Age, Heart rate Systolic blood pressure LVEF Serum creatinine Serum sodium Hemoglobin Diabetes mellitus COPD. In Multivariable Logistic Regression Analysis, After adjustment for confounders, the following variables remained independent predictors of in-hospital mortality**:**

Table no. 2. Multivariable Logistic Regression Model

Variable	Odds Ratio (OR)	95% CI	p-value
Age (per year)	1.05	1.02–1.09	0.001
LVEF (%)	0.93	0.90–0.96	<0.001
Creatinine (mg/dL)	1.78	1.32–2.41	<0.001
Sodium (mmol/L)	0.88	0.82–0.95	0.002
Hemoglobin (g/dL)	0.91	0.84–0.99	0.03
COPD	2.34	1.12–4.88	0.02

Going by the clinical interpretation of the findings of multivariate logistic regression, it was found that age is the strongest demographic predictor, low LVEF is the strongest cardiac predictor, a high level of serum creatinine is a major risk driver, and a low level of serum sodium is a marker of severe heart failure. Amongst co-morbidities, anaemia and chronic obstructive pulmonary disease significantly increase mortality. The predictive performance of the model was evaluated using Receiver Operating Characteristic (ROC) curve analysis. The Area Under the Curve (AUC) was found out to be 0.86 (95% CI: 0.79–0.92) , with a Sensitivity of 83% and Specificity of 78% For the

Hosmer–Lemeshow goodness-of-fit test, p value came out to be 0.41. These findings indicate excellent discriminative ability and good calibration of the mode.

Discussion

This study developed a clinically relevant predictive model for mortality among heart failure patients using routinely available hospital data.. Although the study had a limitation of being from a single tertiary care centre, with a moderate sample size and lacking external validation, the model demonstrated strong discriminatory ability (AUC = 0.86), indicating robust predictive performance

Age and reduced LVEF emerged as key predictors, consistent with prior literature. Renal dysfunction, as reflected by elevated creatinine levels, significantly increased mortality risk, reinforcing the cardiorenal interaction in HF. Hyponatremia and anemia further contributed to adverse outcomes, highlighting systemic involvement in advanced HF.The inclusion of COPD as an independent predictor underscores the role of comorbid respiratory disease in worsening prognosis. Interestingly, lifestyle factors such as smoking and alcohol did not independently predict mortality after adjustment, suggesting that acute clinical parameters may outweigh long-term exposures in hospitalized HF populations.

Compared to existing models, the present model performs favourably while maintaining clinical interpretability. Importantly, it relies only on routinely available variables, enhancing its applicability in resource-limited settings such as India.

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