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SURVIVAL ANALYSIS OF CORONARY HEART DISEASE PATIENTS: THE ROLE OF GENDER, HYPERTENSION, AND CLINICAL RISK FACTORS

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Abstract: Coronary heart disease (CHD) remains a leading cause of morbidity and mortality worldwide, with survival outcomes influenced by multiple demographic and clinical factors. This study aimed to identify prognostic determinants of recovery time among CHD patients using survival analysis. A retrospective dataset of 403 patients with con-firmed CHD was analyzed, excluding incomplete records. Patient characteristics were described, and the Cox proportional hazards model was applied to assess the effect of gender, age, hypertension, diabetes, and prior stroke on recovery time. The proportional hazards assumption was tested, and extended Cox models were considered where nec-essary. The results indicated that male gender and absence of hypertension were sig-nificant predictors of faster recovery, while age, diabetes, and history of stroke did not exhibit significant associations with recovery time. These findings are consistent with recent evidence that sex-related disparities and hypertension status play critical roles in shaping clinical outcomes in CHD patients. The study emphasizes the importance of incorporating these prognostic factors into treatment and rehabilitation planning to op-timize patient management. Nevertheless, the conclusions are limited by the sin-gle-center design and modest sample size, and further multicenter research is recom-mended to confirm these findings and expand their generalizability.

Keywords: coronary heart disease; survival analysis; cox proportional hazards model; prognostic factors; hypertension.

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1. INTRODUCTION

Coronary Heart Disease (CHD) is defined as a heart function disorder caused by insufficient blood supply to the myocardium due to narrowing of the coronary arteries, which leads to inadequate blood flow to the heart muscle [1], [2]. This disease is one of the leading causes of death and disability worldwide [3], [4].

According to the WHO, 70% of global deaths are caused by non-communicable diseases, 45% of which are attributed to heart disease, accounting for 17.7 million out of 39.5 million deaths [5]. The prevalence of CHD based on Riskesdas 2018 was 1.5% [6]. In addition, data from the Sample Registration System (SRS) conducted by the Indonesian Ministry of Health in 2014 indicated that CHD was the second leading cause of death after stroke, contributing to 12.9% of all major causes of death in Indonesia [7]. In Indonesia, aside from its high mortality rate, the number of CHD cases continues to rise, leading to increased national healthcare expenditures. Data from BPJS showed a significant increase in CHD-related healthcare costs from 2014 to 2016 by 68.2%, rising from 4.4 trillion Rupiah in 2014 to 7.4 trillion Rupiah in 2016 [8].

CHD and stroke are closely related, as both are rooted in the process of atherosclerosis, namely the buildup of fatty plaques in blood vessels that cause narrowing and blockage of blood flow. The risk factors for CHD are divided into two categories: modifiable risk factors (which can be altered or controlled through lifestyle changes or treatment) and non-modifiable risk factors (which are related to genetic factors). Controllable risk factors for preventing CHD include hypertension, diabetes, hypercholesterolemia, and body mass index [9], [10].

Survival analysis has become an essential statistical approach in medical research, particularly in studying chronic diseases such as CHD. Unlike conventional regression models, survival analysis accounts for both the time to event and censoring, making it highly relevant for evaluating patient survival and identifying prognostic factors [11]. In the context of CHD, survival analysis can be applied to estimate survival probabilities, evaluate treatment effectiveness, and explore the influence of risk factors on mortality or recovery time.

Several survival models have been widely used to study cardiovascular outcomes. The Cox proportional hazards model is the most frequently applied due to its flexibility in handling both continuous and categorical predictors without requiring assumptions about the baseline hazard function [12]. Furthermore, parametric models such as exponential, Weibull, and log-logistic distributions are often utilized when specific assumptions about the survival time distribution are appropriate [13]. These models provide valuable insights into the relationship between clinical and demographic factors with the survival outcomes of CHD patients.

In Indonesia, research employing survival analysis in CHD is still relatively limited compared to developed countries. Nevertheless, given the increasing prevalence and high burden of CHD, the application of survival models is crucial for identifying high-risk populations and informing evidence-based policies for prevention and treatment [14]. Incorporating predictors such as hypertension, diabetes, hypercholesterolemia, and body mass index into survival models may yield a more comprehensive understanding of patient prognosis and guide more effective clinical interventions.

2. PRELIMINARIES

A. Coronary Heart Disease and Its Global Burden

CHD is one of the leading causes of morbidity and mortality worldwide, primarily resulting from atherosclerosis, a condition characterized by the narrowing of coronary arteries due to plaque buildup. This process leads to reduced blood supply to the myocardium and, consequently, to myocardial ischemia or infarction. Globally, CHD has been recognized as a major public health problem, contributing to millions of deaths annually. In Indonesia, CHD prevalence continues to rise, as reflected in national health surveys and hospital-based reports, making it a critical area for research and prevention strategies [5], [6], [7], [15].

In addition to its high mortality, CHD contributes substantially to years of life lost (YLLs) and years lived with disability (YLDs), creating a significant economic and social burden globally. Recent evidence highlights that low- and middle-income countries, including Indonesia, are experiencing a disproportionate rise in CHD-related morbidity due to rapid urbanization, lifestyle transitions, and limited access to preventive healthcare services [16]. Moreover, projections from global health models suggest that without aggressive intervention strategies, the prevalence of CHD will continue to escalate, driven by aging populations and the increasing prevalence of metabolic risk factors such as diabetes and obesity [17].

B. Survival Analysis in Medical Research

Survival analysis provides an essential statistical framework for analyzing time-to-event data in medical research. Unlike conventional regression models, survival analysis appropriately accounts for censoring and enables estimation of survival probabilities over time. Classical approaches such as the Kaplan–Meier estimator and the log-rank test are frequently used to compare survival distributions between groups, while regression models like the Cox proportional hazards model allow for the examination of multiple predictors simultaneously without requiring assumptions about the baseline hazard [18], [19]. Furthermore, parametric survival models, including exponential, Weibull, and log-logistic distributions, are valuable alternatives when the distribution of survival time follows specific patterns, offering more precise estimates of survival functions [20], [21].

C. Cox Proportional Hazards Model

The Cox proportional hazards (PH) model, introduced by Cox in 1972, is the most widely used method in survival analysis due to its semi-parametric nature, which does not require specification of the baseline hazard function [22]. The model expresses the hazard function for an individual with predictors x as:

$$\mathrm{h}(\mathrm{t}|\mathbf{x}) = \mathrm{h}_0(\mathrm{t})\exp(\mathbf{x}^{\mathrm{T}}\boldsymbol{\beta})$$

where $\mathrm{h}_0(\mathrm{t})$ is the baseline hazard at time t, $\boldsymbol{\beta}$ is a vector of regression coefficients, and $(\mathbf{x}^{\mathrm{T}}\boldsymbol{\beta})$ represents the multiplicative effect of predictors on the hazard. The proportional hazards assumption implies that hazard ratios between groups remain constant over time [23].

Parameter estimation in the Cox model is performed using the partial likelihood method, which eliminates the need to specify the baseline hazard. For observed event times $\mathrm{t_i}$ and corresponding risk sets $\mathrm{R(t_i)}$**,** the partial likelihood is defined as:

$$\mathrm{L_p}(\boldsymbol{\beta}) = \prod_{\mathrm{i},\delta_\mathrm{i}} \frac{\exp(\mathbf{x}_\mathrm{i}{}^{\mathrm{T}}\boldsymbol{\beta})}{\sum_{\mathrm{j}\in\mathrm{R(t_i)}}\exp(\mathbf{x}_\mathrm{j}{}^{\mathrm{T}}\boldsymbol{\beta})}$$

where δ_i indicates whether the event occurred $(\delta_\mathrm{i} = 1)$ or was censored $(\delta_\mathrm{i} = 0)$ The log-partial likelihood $\mathrm{l_p}(\boldsymbol{\beta}) = \log \mathrm{L_p}(\boldsymbol{\beta})$ is maximized to obtain $\widehat{\boldsymbol{\beta}}$, typically via Newton–Raphson or similar iterative algorithms (24). Variance estimates are obtained from the inverse observed information matrix, enabling statistical inference through Wald, score, or likelihood ratio tests.

The regression coefficients in the Cox model are interpreted in terms of hazard ratios (HRs). For a one-unit increase in predictor $(\mathrm{x_k})$**,** holding other variables constant, the hazard ratio is given by:

$$\mathrm{HR} = \exp(\beta_\mathrm{k})$$

A hazard ratio greater than 1 indicates increased risk of the event (higher hazard), while a hazard ratio less than 1 suggests a protective effect (lower hazard). This interpretation of hazard ratios makes the Cox model especially useful for quantifying the relative effect of clinical and demographic predictors on survival outcomes in CHD patients [24].

D. Data Source

The Cox proportional hazards (PH) model, introduced by Cox in 1972, is the most widely used method in survival.

The data used are medical records of CHD patients at the Stroke Center of the DADI Hospital, Labuang Baji Hospital, Haji Hospital, and Pelamonia Hospital in Makassar City, South Sulawesi Province, Indonesia. A total of 440 patients with CHD were initially included in the dataset. Following the exclusion of 37 cases due to missing clinical information, the final sample comprised 403 patients. Table 1 outlines the operational definitions of all variables considered in the study. The variables used in this study consisted of two types, namely responses and predictors. The following is a description of the variables used.

Table 1. Description of Variables Used

Variables	Operational Definition	Scale
Survival time (Y_1)	The time the patient was hospitalized	Ratio
Recovery status (S)	0: Healed/Improved	Nominal
	1: Deceased/Referred to another hospital/Still sick	
Gender (X_1)	0: Male	Nominal
	1: Female	
Age (X_2)	0: $\leq$45 tahun (unrisky)	Nominal
	1: > 45 tahun (risky)	
Hypertension (X_3)	0: No hypertension	Nominal
	1: Hypertension	
Stroke (X_4)	0: No Stroke	Nominal
	1: Stroke	
Diabetes mellitus (X_5)	0: No diabetes mellitus	Nominal
	1: Diabetes mellitus	

E. Research Procedures

The research procedure consisted of several stages to analyze the survival of CHD patients. First, patient characteristics were described according to clinical and demographic factors that may influence survival outcomes. Subsequently, the dependent variable, survival time, was examined to understand its distribution. The proportional hazards assumption was then evaluated, either through global testing or goodness-of-fit analysis, to identify potential violations. In cases where the assumption was not satisfied, an Extended Cox regression model was applied to accommodate time-dependent effects. Model parameters were estimated and tested for statistical significance, and the most appropriate Cox model was selected based on these results. Finally, hazard ratios were interpreted to determine the relative impact of each prognostic factor on the survival of CHD patients.

3. MAIN RESULTS

A. Descriptive Statistics

The study begins by examining the characteristics of all variables used, including both the response and predictor variables. The first step involves analyzing the characteristics of the response variable data using descriptive statistics, specifically the survival time, with the results presented in the table below.

Table 2. Descriptive statistics of survival time variable

Variable	Min	Max	Mean	Median	Mode	Std. Deviation
Survival Time (Y)	0	68	5.2416	5	4	3.3903

Based on Table 2 above, the duration of hospitalization for patients with CHD ranges from a minimum of 0 days to a maximum of 68 days. On average, patients are hospitalized for 5 days, with the most frequent duration being 4 days. Secondly, the characteristics of the predictor variables are illustrated in the figure below.

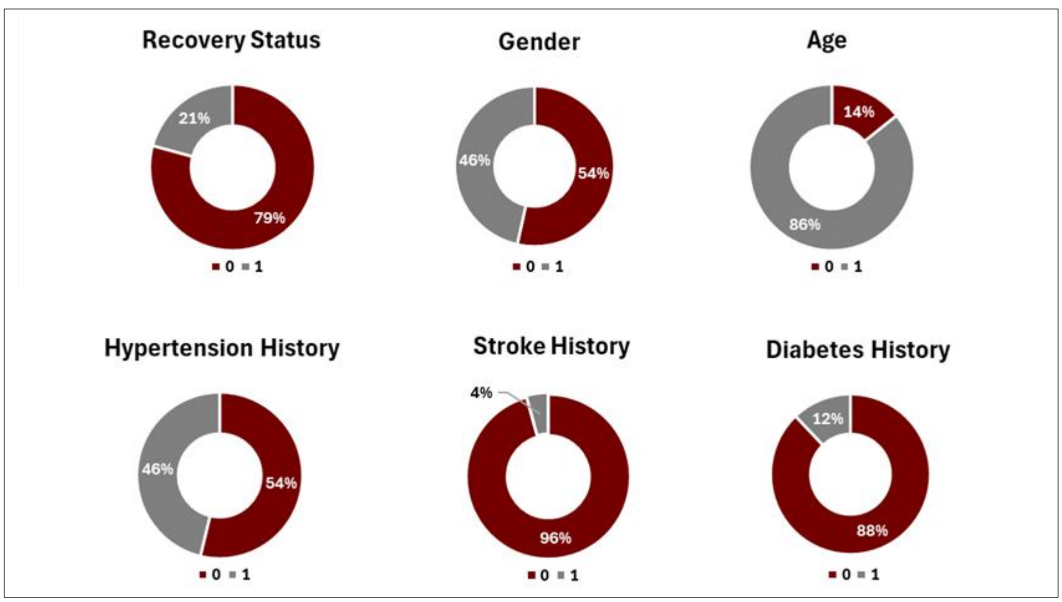

Figure 1. Pie chart of predictor variables

Based on Figure 1, it is observed that among coronary heart disease patients treated at DADI Hospital, Labuang Baji Hospital, Haji Hospital, and Pelamonia Hospital in Makassar City, South Sulawesi Province, Indonesia, 79% recovered or showed improvement. Male patients accounted for 8% more than female patients. Furthermore, 86% of the patients were over 45 years old, 54% had a history of hypertension, only 4% had no history of stroke, and 12% were without diabetes mellitus.

B. Cox Proportional Hazard Model

Before conducting modeling using the Cox proportional hazards regression, the first step is to test the proportional hazards assumption by utilizing the log-minus-log (LML) function. The results of the assumption test are presented in Table 3 below.

Table 3. Test of the Proportional Hazards Assumption for Predictor Variables

Variables	Proportional Hazard Assumption
Gender $(\mathbf{X_1})$	passed
Age $(\mathbf{X_2})$	passed
Hypertension History $(\mathbf{X_3})$	passed
Stroke History $(\mathbf{X_4})$	passed
Diabetes History $(\mathbf{X_5})$	passed

All five predictor variables satisfy the proportional hazards assumption. As an example, the LML function curves for the variables age and stroke history are presented below.

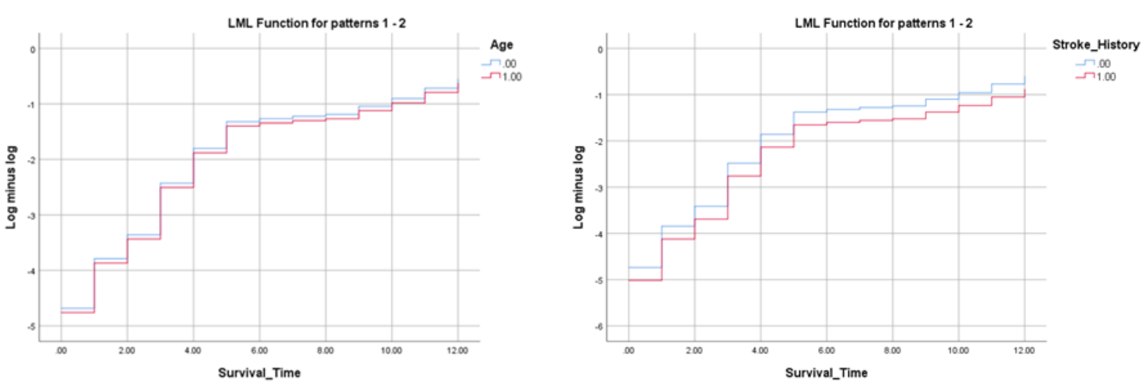

Figure 2. Log-Minus-Log (LML) Function Curves for Age and Stroke History

Based on Figure 2, the LML curves for the age variable appear parallel, indicating that the hazard ratio remains constant over time between the age groups of 45 years and below and above 45 years. Similarly, for the stroke history variable, the curves for patients with and without a history of stroke are also parallel, with a constant hazard ratio over time. These results indicate that the proportional hazards assumption is fulfilled.

After testing the proportional hazards assumption, the next step is to model the survival time of patients with coronary heart disease (CHD) using the Cox proportional hazards model, with the reference category set as the last category (coded as 1), namely female, older than 45 years, and having a history of hypertension, stroke, and diabetes. The results obtained are as follows.

Table 4. Results of the Cox Proportional Hazards Model

Variables	Coef. (β)	SE	Wald Test	df	Sig.	Exp (β)	95.0% CI for Exp (β)	
							Lower	Upper
Gender (X_1)	0.435	0.165	6.949	1	0.008*	1.545	1.118	2.136
Age (X_2)	0.078	0.224	0.121	1	0.728	1.081	0.697	1.676
Hypertension History (X_3)	0.39	0.168	5.414	1	0.02*	1.477	1.063	2.051
Stroke History (X_4)	0.278	0.42	0.438	1	0.508	1.321	0.579	3.01
Diabetes History (X_5)	0.328	0.272	1.455	1	0.228	1.388	0.815	2.366

The results of the survival time modeling for CHD patients treated at DADI Hospital, Labuang Baji Hospital, Haji Hospital, and Pelamonia Hospital in Makassar City, South Sulawesi, using five predictor variables, as presented in Table 4, can be interpreted as follows:

1. Gender

The gender variable showed a coefficient of 0.435 with a p-value of 0.008, indicating a statistically significant effect at the 5% level. The hazard ratio of 1.545 (95% CI: 1.118–2.136) suggests that, compared to female patients, male patients have a 54.5% higher hazard of recovery or clinical improvement during hospitalization, after adjusting for age, hypertension, stroke, and diabetes history. This implies that male patients tend to recover or be discharged faster than female patients.

2. Age

The age variable has a coefficient of 0.078 and a p-value of 0.728, with a hazard ratio of 1.081 (95% CI: 0.697–1.676). Although patients aged 45 or younger show an 8.1% higher hazard of recovery compared to those older than 45, this effect is not statistically significant, indicating no clear impact of age on recovery time in this model.

3. Hypertension History

The coefficient for hypertension history is 0.390 with a p-value of 0.020, indicating a statistically significant effect. The hazard ratio of 1.477 (95% CI: 1.063–2.051) shows that patients without hypertension have a 47.7% higher hazard of recovery or discharge compared to those with hypertension, after adjusting for other factors. This suggests faster recovery for non-hypertensive patients.

4. Stroke History

The coefficient for stroke history is 0.278 with a p-value of 0.508, and a hazard ratio of 1.321 (95% CI: 0.579–3.010). Although patients without stroke history show a 32.1% higher hazard of recovery, this effect is not statistically significant, indicating no clear impact of stroke history on recovery time.

5. Dibetes History

The diabetes history coefficient is 0.328 (p = 0.228) with a hazard ratio of 1.388 (95% CI: 0.815–2.366). Although patients without diabetes show a 38.8% higher hazard of recovery, the effect is not statistically significant.

Based on the five points above, it can be concluded that being male and not having a history of hypertension are statistically significant predictors associated with a shorter time to recovery or discharge among patients with coronary heart disease (CHD). In contrast, age, stroke history, and diabetes history do not show statistically significant associations with recovery time in this model. So, the Cox proportional hazards model can be expressed as follows:

$$\mathrm{h}(\mathrm{t}|\mathbf{x}) = \mathrm{h}_0(\mathrm{t})\exp(0.435 \times \mathrm{Gender} + 0.390 \times \mathrm{Hypertension\ History})$$

C. Discussion

This study aimed to identify factors influencing the recovery time of CHD patients using the Cox proportional hazards model. By including variables such as gender, age, history of hypertension, stroke, and diabetes, our results showed that male gender and absence of hypertension history were significant predictors of shorter recovery times, whereas age, history of stroke, and history of diabetes did not show significant associations.

Our finding that male gender is associated with more favorable recovery is supported by recent literature. Smith et al. (2022) reported that females with coronary artery disease often have worse short-term outcomes compared to males, including lower improvement after rehabilitation programs [25]. Moreover, a 2025 review by Knox et al. highlighted that women are less likely to receive guideline-recommended medications (e.g. statins, ACE inhibitors) and invasive treatments, which may contribute to worse clinical trajectories in CHD [26]. These disparities in management could partly explain the gender differences in recovery observed in our study.

In terms of hypertension, our result that the absence of hypertension is associated with better recovery aligns with the broader understanding of hypertension as a risk factor for adverse cardiovascular outcomes. Hypertension induces structural and functional changes in the vasculature and myocardium such as right ventricular remodeling, arterial stiffness, endothelial dysfunction that increase the risk of ischemic events, limit the reserve capacity of cardiac tissue, and slow the healing or remodeling process after coronary injury. Several recent studies underscore that high blood pressure control remains a critical target for improving outcomes in CHD patients (e.g. in meta-analyses of secondary prevention).

It is interesting that in our cohort, age, prior stroke, and diabetes did not emerge as significant predictors of recovery time, despite this being commonly documented in many studies. This discrepancy may be due to effective management protocols, close monitoring, or selection bias in our hospital dataset. Alternatively, it may reflect that, once acute management is successful, gender and hypertension status exert more dominant influence on short-term recovery trajectories.

From a mechanistic standpoint, sex differences in CHD outcomes may be influenced by hormonal modulation, differential myocardial remodeling, microvascular function, and inflammatory/oxidative stress responses. For example, female patients may lose the protective effects of estrogens post-menopause, leading to more diffuse and microvascular coronary disease, which is more difficult to treat than focal lesions [27]. In addition, procedural complications differ by sex; a recent study showed that women experience higher bleeding risk and vascular complications after percutaneous coronary interventions (PCI) compared to men, potentially affecting recovery, and requiring more cautious post-procedure care [28].

Given these findings, our study reinforces the need for sex-aware management pathways in CHD care. For male and female patients, differential strategies—such as optimization of hypertension control, more aggressive secondary prevention in women, and tailored rehabilitation—may improve recovery profiles. However, our findings are limited by the single-region design and moderate sample size, which restrict generalizability.

4. CONCLUSIONS

This study applied the Cox proportional hazards model to identify prognostic factors influencing the recovery time of patients with coronary heart disease (CHD). The analysis demonstrated that male gender and the absence of a history of hypertension were sig-nificant predictors of faster recovery, while age, prior stroke, and diabetes did not show significant effects. These findings underscore the importance of considering sex-specific differences and hypertension status in the clinical management and rehabilitation planning of CHD patients. Tailored treatment and follow-up strategies based on these factors may help optimize patient outcomes. However, given the limited sample size and the single-center setting, caution is warranted in generalizing the results. Further mul-ticenter studies with larger and more diverse populations are needed to validate these findings and to explore additional clinical and lifestyle factors that may influence recovery trajectories in CHD patients.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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