Eduvest – Journal of Universal Studies
Volume 6 Number 8, August, 2026
p- ISSN 2775-3735- e-ISSN 2775-3727

Survival Analysis of Tuberculosis Patients Among National Health Insurance Participants, 2015–2024

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Keywords
Tuberculosis, Survival Analysis, Kaplan-Meier, Cox Proportional Hazard, Accelerated Failure Time, BPJS Kesehatan, Time to Death

ABSTRACT
Indonesia ranks second globally in TB incidence, with an estimated 1 million new cases annually. The majority of TB patient care costs in Indonesia are covered through the National Health Insurance program administered by BPJS Kesehatan. This research aims to analyze the time to death pattern of TB patients enrolled in JKN, identify the factors influencing it, and compare the performance of the Cox PH and AFT models. The data used are BPJS Kesehatan sample data from the 2015–2024 period, with an observation window from January 1, 2022 to December 31, 2024. The analysis was conducted on 111,946 patients, consisting of 10,083 patients (9.01%) who died and 101,863 patients (90.99%) who were censored. Analysis was carried out sequentially using the Kaplan-Meier method, the Cox PH Model, and the AFT Model with the Weibull distribution selected based on the best AIC, BIC, and Log-Likelihood values. Results showed a mean survival time of 879 days among TB patients. Age was the most dominant factor; patients above 60 years of age had a hazard ratio 8.09 times higher and a survival time 76% shorter compared to the 0–35 age group. Female patients had a survival time 28% longer than male patients. The PBI JK segment showed the highest mortality risk, while patients in Domicile 4 and 5 had shorter survival times compared to Domicile 1. The Schoenfeld residual test rejected the proportional hazards assumption, rendering the Weibull AFT model the most appropriate and best-fitting for this study.

INTRODUCTION

Tuberculosis (TB) is still one of the infectious diseases with the highest morbidity and mortality burden in the world. A World Health Organization report shows that TB is consistently the leading cause of death from infectious diseases with millions of new cases and more than one million deaths each year, especially in low- and middle-income countries (WHO: 2023). Despite the availability of effective treatments, studies have shown that the clinical outcomes of TB patients still vary and some patients remain at significant risk of death during treatment and follow-up.

WHO data (2025) states that as many as 30 countries with a high TB burden account for 87% of all estimated incidence cases worldwide. While 8 countries contributed the equivalent of 67%, the details were India (25%), Indonesia (10%), the Philippines (6.8%),

China (6.5%), Pakistan (6.3%), Nigeria (4.8%), Democratic Republic of Congo (3.9%), and Bangladesh (3.6%).

Currently, Indonesia is still one of the countries that contribute to a large number of tuberculosis cases in the world. Based on the official Global Tuberculosis Report (2024) published by WHO, Indonesia reportedly has an estimated very high number of TB cases compared to other countries. This is the reason why Indonesia is categorized as a high tuberculosis burden country. WHO data shows that in the last ten years, the number of TB cases in Indonesia has remained at a high level with an estimated incidence of hundreds of cases per 100,000 population per year and relatively limited fluctuations. The global findings are in line with national data published by the Ministry of Health of the Republic of Indonesia which shows that the burden of TB disease in Indonesia is still high and is a major challenge for the national health system. The consistency between the data of WHO and the Indonesian Ministry of Health confirms that TB control in Indonesia requires an analytical approach that not only focuses on the number of cases, but also on the dynamics of the time of incidence and clinical outcomes of TB patients nationally. Global Tuberculosis Report data from 2016 to 2025 shows that the estimated number of Tuberculosis cases in Indonesia is still in the range of 1 million cases per year, and there are no signs of a downward trend.

A survival study conducted by Liu et al. (2022) showed that the survival probability of TB patients was significantly influenced by demographic and clinical factors in which patients of advanced age, male gender, and individuals with low socioeconomic status had a higher risk of death. In addition, clinical factors such as previous TB treatment history, positive bacteriological status, delayed diagnosis, and disease severity at the beginning of treatment have also been shown to increase the risk of death. The findings are reinforced by large-scale cohort research conducted by Vélez-Gómez et al. (2025) which showed that advanced age, male sex, HIV coinfection, diabetes mellitus, previous TB treatment history, as well as socioeconomic factors are significantly associated with increased mortality of TB patients.

The results of these studies confirm that TB is a disease that is influenced by a combination of demographic, clinical, and social factors, and has strong time-to-event characteristics, so it requires a time-to-event survival analysis approach to comprehensively understand the dynamics of patient survival.

Tuberculosis is a disease that requires a relatively long duration of treatment, so it has a direct impact on the financial burden of health services. According to WHO, treatment of drug-sensitive TB generally takes at least six months. Meanwhile, drug-resistant tuberculosis requires a much longer duration of therapy, which is up to 18–24 months. The long duration of treatment has implications for increasing direct medical costs, such as outpatient costs, hospitalization, medications, and other supporting examinations. In addition, there is also an increase in indirect costs borne by patients and the health system. A study conducted by Tanimura et al. (2014) shows that the length of TB treatment significantly increases the financial burden, even causing catastrophic health expenditure in most TB patients in low- and middle-income countries.

Similar findings in the Indonesian context are also shown by Fuady et al. (2019) who found that the long duration of TB treatment contributes greatly to the increasing burden of health costs, both borne by the patient's household and by the national health financing system. This condition shows that the length of time until clinical outcomes are achieved in TB patients

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not only has an impact on health aspects, but also has significant economic implications. Therefore, time-to-event-based analysis is important to understand and control TB's financial burden more effectively.

The burden of tuberculosis in Indonesia not only has an impact on public health aspects, but also poses significant financial pressure on the national health financing system. In the Indonesian context, TB health service financing is mostly borne by BPJS Kesehatan through the National Health Insurance (JKN) scheme, especially for outpatient services, hospitalization, medicines, and supporting examinations at health facilities. Reports and policy documents published by the Ministry of Health of the Republic of Indonesia show that TB is one of the important contributors to the burden of financing hospital health services, especially due to the long duration of treatment and the need for repeated treatments. A study conducted by Tanimura et al. (2014) shows that the length of duration of TB treatment contributes significantly to the increase in health care costs and creates a huge financial burden on the health system in low- and middle-income countries. These findings are in line with the Indonesian context as shown by research by Fuady et al. (2019) which found that although Indonesia has implemented health coverage through JKN, TB disease still poses a substantial cost burden for the health system and households, especially in cases with longer treatment durations. This condition confirms that understanding the factors that affect the length of TB treatment time is crucial not only from a medical perspective, but also from the perspective of the sustainability of national health financing.

In epidemiological and clinical research, particularly in diseases with time-to-event characteristics such as tuberculosis, various survival analysis approaches have been used to study survival and duration of disease occurrence. According to Kleinbaum and Klein (2020), non-parametric methods such as Kaplan–Meier and Nelson–Aalen are the basic approaches that are widely used to descriptively estimate survival and hazard functions without assuming a specific form of distribution. Kaplan–Meier is used to describe the probability of survival over time. On the other hand, Nelson-Aalen focuses on estimating the accumulation of hazard events. Kleinbaum and Klein (2020) also assert that the non-parametric approach has limitations because it cannot accommodate the simultaneous influence of various risk factors. To overcome these limitations, the semi-parametric Cox Proportional Hazards model is widely used in medical research and epidemiology because it allows multivariate analysis and generates hazard ratio estimates of factors that affect the risk of events.

The differences in characteristics and assumptions in each survival model suggest that there is no one universally superior approach for all types of data and clinical contexts. According to Kleinbaum. D. G.. & Klein. M. (2020), the selection of the right survival model must consider the purpose of analysis, data structure, the existence of censorship, and the fulfillment of model assumptions. Non-parametric approaches such as Kaplan–Meier and Nelson–Aalen are beneficial for early exploration and visualization of survival patterns, but inadequate for multivariate inference. The semi-parametric model of Cox Proportional Hazards offers flexibility and ease of interpretation through hazard ratios, but its reliance on the assumption of proportional hazards can limit the accuracy of estimates as risks change over time. Under these conditions, parametric models such as Accelerated Failure Time (AFT) provide a relevant alternative because they model the time of occurrence directly and allow for duration-based interpretation, which is aligned with the needs of time-to-death analysis.

This study was conducted to analyze the time to death pattern of tuberculosis patients participating in the National Health Insurance Program (JKN) based on BPJS Kesehatan sample data in 2015–2024, as well as identify factors that affect the time of death using the Cox Regression and Accelerated Failure Time (AFT) methods. In addition, this study aims to compare the two methods to determine the most appropriate model in estimating the duration of survival of tuberculosis patients. The results of the research are expected to be an input for the Ministry of Health and BPJS Kesehatan in the formulation of tuberculosis control policies and the improvement of health services, as well as a reference for further research in the field of health and actuarial. The analysis was carried out using BPJS Kesehatan sample data for the 2015-2024 period with variables limited to the available data, and only considered deaths due to tuberculosis as events, while deaths due to other diagnoses were treated as censored data. Through a comparison of the Kaplan–Meier, Nelson–Aalen, Cox Proportional Hazards, and AFT methods, this study seeks to obtain the most accurate and informative model to support clinical decision-making and health policy.

METHOD

This study used sample data of participants in the National Health Insurance Program (JKN) managed by BPJS Kesehatan. The research sample consisted of 118,747 participants who were diagnosed with tuberculosis and received health services during the 2015–2024 period. The variables analyzed included time to death as a dependent variable, as well as age group, gender, BPJS Kesehatan membership segment, and residential domicile as independent variables. The data also took into account the censoring conditions, namely participants who were still alive or out of the program during the observation period.

Data analysis was carried out using R software through two stages. The first stage is a descriptive analysis to describe the characteristics of the patient based on age, gender, membership segment, domicile, and final status of the patient. The second stage is survival analysis to assess the survival time of tuberculosis patients until death or the end of the observation period.

Survival analysis was carried out using three approaches, namely the Kaplan-Meier method to estimate the chances of survival and compare the survival curve between groups, the Cox Proportional Hazards model to identify factors that affect the risk of death, and the Accelerated Failure Time (AFT) model to analyze the influence of variables on the length of the patient's survival time. The best AFT model is selected based on AIC, BIC, and Log-Likelihood values so that the most appropriate model is obtained in explaining the time to death of tuberculosis patients participating in JKN.

RESULT AND DISCUSSION

Descriptive Analysis

In this study, the observation date was set from January 1, 2022 to December 31, 2024. Based on initial sample data, there were 118,747 history of tuberculosis patients with the final status of death and life. There were 6,801 data that were assumed to be truncation and were not included in the survival analysis because the date of death was smaller than the date of observation. Thus, the data used in the survival analysis was as many as 111,946 patients with

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details of 10,083 patients (90.99%) who died in the observation period and 101,863 patients (9.01%) who were still alive until the end of the observation date.

When viewed from the age grouping, Tuberculosis patients have a diverse age distribution in each age group. The most patients were people in the productive age of 0-35 years with a proportion of 48.25%. The least patient is the age group > 60 years old with a proportion of 17.89%. However, when viewed from the number of patients who died, it can be seen that the higher a person's age, the more risk of death. A total of 86.53% of deaths occurred in patients in the age group of 36-60 years and > 60 years, respectively at 41.08% and 45.45%.

Judging from the proportion of gender, it can be seen that male patients account for 53.57% and women 46.43%. Of all patients who died, 64.29% were male patients and 35.71% were female.

In the membership segment, data was obtained that the most participants were the PPU segment with 27.03%, followed by the Local Government PBPU with 25.61%. Meanwhile, the PBI JK segment only accounted for 4.71% of participants. Then of all patients who died, as many as 27.82% of them were in the PPU segment, followed by the Non-Worker segment as much as 24.73%.

When viewed from Domicile, data was obtained that the majority of patients, namely 65.66%, came from Domicile 1 and Domicile 2 with details of 31.05% and 29.59%, respectively. The same thing happened in the number of patients who died, where as many as 60.64% of patients who died came from Domicile 1 and Domicile 2 with details of 32.05% and 29.59% respectively.

The details of the research data can be seen in the following table:

Table 1. Details of Tuberculosis Patient Sample Data

Description	Deceased Patients		Surviving Patients		Total Patients	
	Count	%	Count	%	Count	%
Age Group						
0 - 35	1,358	13.47%	52,659	51.70%	54,017	48.25%
36 - 60	4,142	41.08%	33,761	33.14%	37,903	33.86%
> 60	4,583	45.45%	15,443	15.16%	20,026	17.89%
Total	**10,083**	**100%**	**101,863**	**100%**	**111,946**	**100%**
Gender						
Male	6,482	64.29%	53,486	52.51%	59,968	53.57%
Female	3,601	35.71%	48,377	47.49%	51,978	46.43%
Total	**10,083**	**100%**	**101,863**	**100%**	**111,946**	**100%**
Membership Segment						
PBI JK (Subsidized Beneficiaries)	1,311	13.00%	3,964	3.89%	5,275	4.71%
PBPU Pemda (Local Govt Subsidized)	1,378	13.67%	27,292	26.79%	28,670	25.61%
PPU (Formal Wage Earners)	2,805	27.82%	27,456	26.95%	30,261	27.03%
PBPU (Informal / Self-Employed)	2,095	20.78%	21,648	21.25%	23,743	21.21%
Non-Worker	2,494	24.73%	21,503	21.11%	23,997	21.44%
Total	**10,083**	**100%**	**101,863**	**100%**	**111,946**	**100%**
Residence / Domicile Location						
Domicile 1	3,132	31.05%	35,949	35.29%	39,081	34.91%
Domicile 2	2,984	29.59%	31,436	30.86%	34,420	30.75%
Domicile 3	1,024	10.16%	10,560	10.37%	11,584	10.35%
Domicile 4	1,653	16.39%	12,370	12.14%	14.023	12.53%
Domicile 5	1,290	12.79%	11,548	11.34%	12,838	11.47%

Total	**10,083**	**100%**	**101,863**	**100%**	**111,946**	**100%**

Source: BPJS Kesehatan sample data, processed by the author (2026)

Survival Analysis

Based on the data of the research sample, out of a total of 111,946 patients, as many as 10,083 patients or 9.01% died during the observation period and the remaining 101,863 patients or 90.99% were still alive until the end of the observation date. As explained at the beginning, the observation period is the time range between January 1, 2022 to December 31, 2024.
Based on the survival analysis using R software, the following results were obtained:

Table 2. Survival Analysis Output

Estimate	**Std. Error**	**95% Confidence Interval**	
		Lower Bound	**Upper Bound**
879.123	0.420253	877.697	879.345

Source: Author's data processing (2026) using R software

Based on the above results, it can be seen that the average survival time of Tuberculosis patients in this study is around 879 days (2.4 years). The standard error generated is very small, which is 0.420253. This shows that the calculation results are very stable because the sample used is quite large.

With a 95% Confidence Interval, the average survival time of Tuberculosis patients is in the range of 877 days to 879 days.

Kaplan-Meier analysis

Survival analysis is a statistical method used to study the time until the occurrence of a certain event (event), which in this study is defined as death in tuberculosis patients. One of the non-parametric approaches that is widely used in analysis is the Kaplan-Meier method. This method allows estimation of survival function without requiring assumptions about certain forms of distribution, and is able to handle data that contains censorship commonly found in health data.

In this study, the Kaplan-Meier method was applied to estimate the probability of survival of National Health Insurance (JKN) participants suffering from tuberculosis during the observation period. The results of these estimates provide an initial picture of the patient's survival patterns and subsequently form the basis for the development of further analyses using more complex models, such as Cox Proportional Hazards.

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1. **Age Covariate**

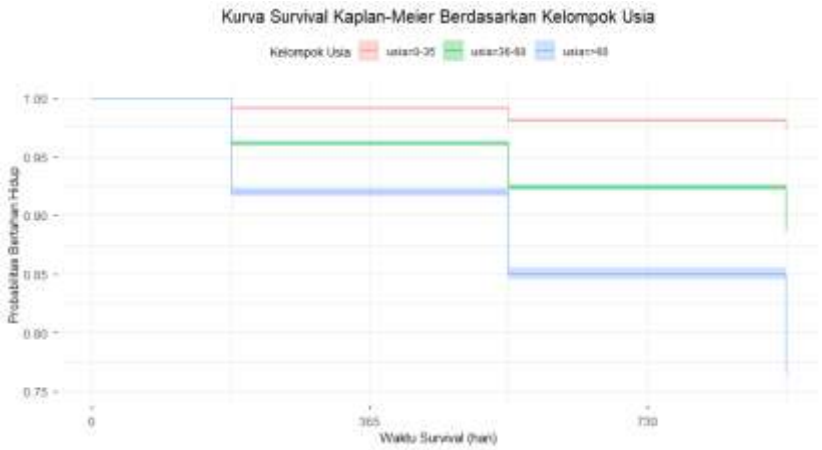

Figure 1. Kaplan-Meier Survival Function Graph for Age Group Factors.
Source: Author's data processing (2026) using R software

Figure 1 shows a graph of the Kaplan-Meier survival function for the age group factor. In the age group factor, it can be seen that the lowest survival time is in the age group of >60 years with an average survival time of 828 days. The second lowest survival time is for the age group of 36 – 60 years with an average survival time of 870 days. Furthermore, the age group of 0 – 35 years has the best survival time, which is 902 days.

2. **Sex Covariates**

Figure 2. Kaplan-Meier Survival Function Graph for Sex Factor.
Source: Author's data processing (2026) using R software

Figure 2 shows a graph of the Kaplan-Meier survival function for the sex factor. It was seen that patients with the male sex had a lower survival time compared to women. Male Tuberculosis patients have a survival time of 871 days, while Female is 887 days.

3. **Membership Segment Covariates**

Figure 3. Kaplan-Meier Survival Function Graph for Membership Segment Factors.
Source: Author's data processing (2026) using R software

Figure 3 shows a graph of the Kaplan-Meier survival function for the participation segment factor. In the membership segment factor, it can be seen that the lowest survival time is in the PBI JK segment with an average survival time of 830 days. The second lowest survival time is for the PBPU segment with an average survival time of 872 days. Furthermore, the survival time for the Non-Worker and PPU segments is 876 days and 880 days, respectively. Finally, the PBPU segment of the Regional Government has the best survival time, which is 891 days.

4. **Covariate Domicile**

Figure 4. Kaplan-Meier Survival Function Graph for Domicile Factors
Source: Author's data processing (2026) using R software

Figure 4 shows a graph of the Kaplan-Meier survival function for domicile factors. In the domicile factor, it can be seen that the lowest survival time is in patients from Domicile 4 with an average survival time of 865 days. The second lowest survival time is for Domicile 5 with an average survival time of 873 days. Furthermore, Domicile 3 and Domicile 2 have an average

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survival time of 879 and 880 days, respectively. Finally, Domicile 1 is the domicile with the best average survival time, which is 882 days.

Next, a Log-Rank Test will be carried out: The log-rank test is used to test whether there is a difference in survival function between groups based on certain covariates on the Kaplan-Meier curve. The results of this test are the initial basis for identifying covariates that have significant survival differences before survival regression modeling using the Cox Proportional Hazards and Accelerated Failure Time models.

The following is a recapitulation of the results of the Log-Rank Test.

Table 3. Log-Rank Test Results

Description	Chi-square	df	p-value
Age Group	7529,04	2	<0.001
Gender	539,65	1	<0.001
Membership Segment	2279,7	4	<0.001
Domicile of Residence	203,66	4	<0.001

Source: Author's data processing (2026) using R software

The results of the Log-Rank test in table 3 show that there are significant differences in the survival curve for the covariates of Age Group, Gender, Membership Segment, and Domicile.

Analysis Cox Proportional Hazard

Although the Kaplan-Meier analysis provides an initial picture of patient survival patterns, the method is descriptive and limited to comparisons between groups on an individual basis. To gain a more comprehensive understanding of the factors that affect the risk of mortality, an analytical approach that is able to accommodate several variables simultaneously is needed.

In this study, the Cox Proportional Hazards model was used as a follow-up analysis method. This model is a semi-parametric approach used to examine the influence of various covariates on hazard or the risk of an event, without assuming a specific form of baseline hazard distribution. Thus, the Cox model allows an estimate of the magnitude of the influence of each variable on the risk of death of tuberculosis patients participating in the National Health Insurance (JKN).

First of all, a proportional hazards assumption test is carried out first (residual Schoenfeld test). The goal is to ensure that the hazard ratio is constant over time.

Table 4. Results of the Proportional Hazards Assumption Test (Schoenfeld Residual Test)

Covariate	Chi-Square	df	p-value	Assumption of Proportional Hazards Met/Not
Age	13,8	2	0,00099	no
Gender	1,9	1	0,16753	yes
Segment	203,2	4	< 0.001	no
Domicile	13,3	4	0,00998	no
Global	216,9	11	< 0.001	no

Source: Author's data processing (2026) using R software

In table 4, it can be seen that the sex covariate meets the assumption of proportional hazards at alpha 5%, because it has a p-value greater than 0.05. On the other hand, the Age, Segment and Domicile covariates showed a p-value result smaller than 0.05, so it did not meet the assumption of Proportional Hazards. Overall, the model does not meet the assumption of proportional hazards because the global p-value is smaller than 0.05.

Furthermore, the main output results of the Cox Proportional Hazards model will also be seen.

Table 5. Key Output Results of the Cox Proportional Hazards Model

Variable	Coefficient (B)	SE	Z	Sig	Exp B (Hazard Ratio)
Age					
36 -60	1,45	0,03	46,07	<0.001	4,25
> 60	2,09	0,03	63,81	<0.001	8,09
Gender (P)	-0,35	0,02	-16,90	<0.001	0,70
Membership segment					
PBI JK	0,45	0,03	13,07	<0.001	1,57
PBPU	0,20	0,03	6,82	<0.001	1,22
PBPU Local Government	-0,18	0,03	-5,16	<0.001	0,84
Non-Employees	0,22	0,03	7,80	<0.001	1,24
Domicile of Residence					
Domicile 2	0,01	0,03	0,43	0,6706	1,01
Domicile 3	0,08	0,04	2,10	0,0356	1,08
Domicile 4	0,20	0,03	6,52	<0.001	1,22
Domicile 5	0,22	0,03	6,60	<0.001	1,25

Source: Author's data processing (2026) using R software

Based on the model output, the Cox Proportional Hazard model was obtained as follows: h(t,x) = exp (1.45 Age 36 - 60 years + 2.09 Age > 60 years old - 0.35 Female Gender + 0.45 PBI JK Segment + 0.20 PBPU Segment - 0.18 Local Government PBPU Segment + 0.22 Non-Worker Segment + 0.08 Domicile 3 + 0.20 Domicile 4 + 0.22 Domicile 5.

The explanation of each variable is as follows:

1. Age Covariate

a. Age Covariate 36–60 years (Coefficient = 1.45)
Hazard Rate = This means that by controlling for other covariates, individuals in the age group of 36–60 years have a 4.25 times higher risk of occurrence compared to individuals in the reference age category (0–35 years).$e^{1,45} \approx 4,25$.

b. Age Covariate > 60 years (Coefficient = 2.09)
Hazard Rate = $e^{2,09} \approx 8,09$. This means that by controlling for other covariates, individuals with an age group over 60 years have an event risk/hazard of 8.09 times higher than individuals in the reference age category (0–35 years).
The following is a graph illustrating the difference in survival probabilities between age groups.

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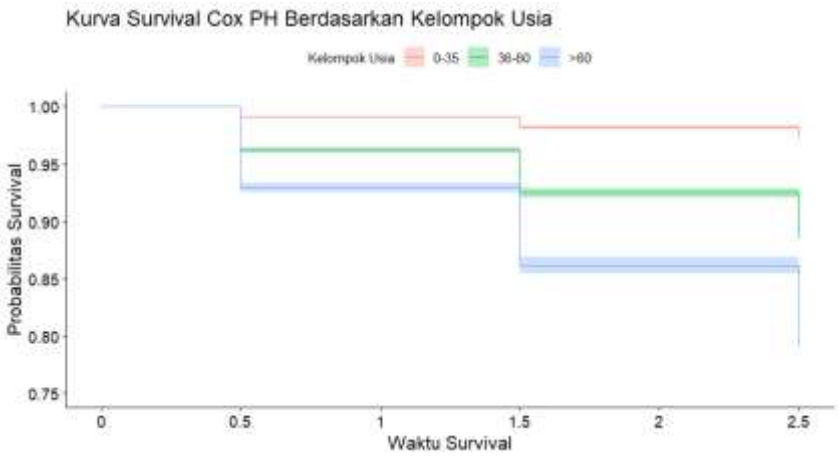

Figure 5. Cox PH Survival Curve by Age Group

Source: Author's data processing (2026) using R software

The survival curve based on the Cox Proportional Hazard model showed a clear separation between age groups throughout the observation period. The 0–35 age group consistently had the highest probability of survival, followed by the 36–60 age group, while the age group over 60 years showed the lowest probability of survival. This pattern indicates a strong association between increasing age and a decrease in survival chances. The consistency of this curve separation reinforces that age is a major determinant factor in the risk of patient death.

2. Sex Covariates

Female Sex Covariate (Coefficient = -0.35)

Hazard Rate = . This means that by controlling for other covariates, female individuals have 0.70 times or 30% lower risk of occurrence compared to male individuals (reference category).$e^{-0,35} \approx 0,70$

The following is a graph illustrating the difference in survival probabilities between sex groups.

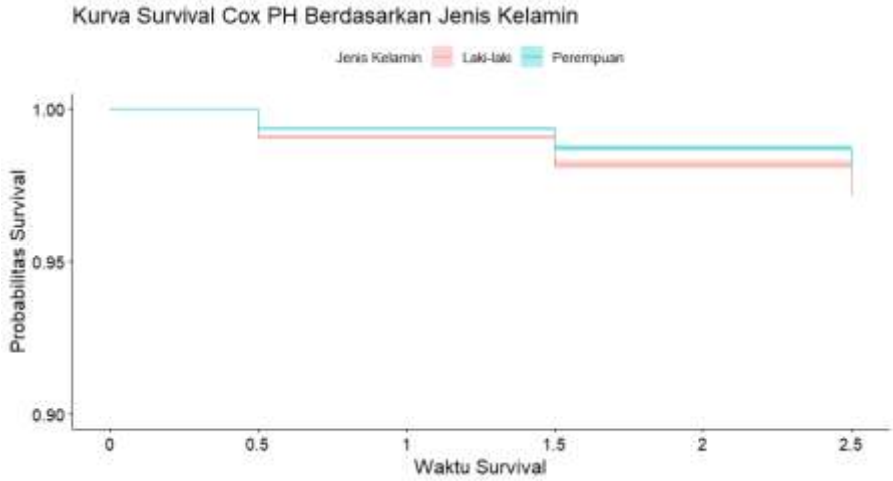

Figure 6. Cox PH Survival Curve by Sex

Source: Author's data processing (2026) using R software

The survival curve based on the Cox Proportional Hazard model shows that there is a difference in the probability of survival between male and female patients. Throughout the observation period, the female group consistently had a slightly higher probability of survival than the male. Although the difference in curves is not very large, this pattern suggests that gender has an influence on a patient's chances of survival. These results are in line with Cox's regression analysis which shows that women have a lower risk of death than men.

3. Membership Segment Covariates

a. PBI JK Segment Covariate (Coefficient = 0.45)

Hazard Rate = . This means that by controlling for other covariates, individuals with the PBI JK segment have a 1.57 times higher incidence risk/hazard compared to individuals in the reference segment (PPU).$e^{0,45} \approx 1,57$

b. PBPU Segment Covariate (Coefficient = 0.20)

Hazard Rate = . This means that by controlling for other covariates, individuals with the PBPU segment have a 1.22 times higher incidence risk compared to individuals in the reference segment (PPU).$e^{0,20} \approx 1,22$

c. Local Government PBPU Segment Covariate (Coefficient = - 0.18)

Hazard Rate = . This means that by controlling for other covariates, individuals with the PBPU segment of the Regional Government have an incidence risk/hazard of 0.84 times or lower compared to individuals in the reference segment (PPU).$e^{-0,18} \approx 0,84$

d. Non-worker segment covariate (coefficient = 0.22)

Hazard Rate = . This means that by controlling for other covariates, individuals with the non-worker segment have a 1.24 times higher risk of occurrence compared to individuals in the reference segment (PPU).$e^{0,22} \approx 1,24$

The following is a graph that illustrates the difference in survival probability between groups of membership segments.

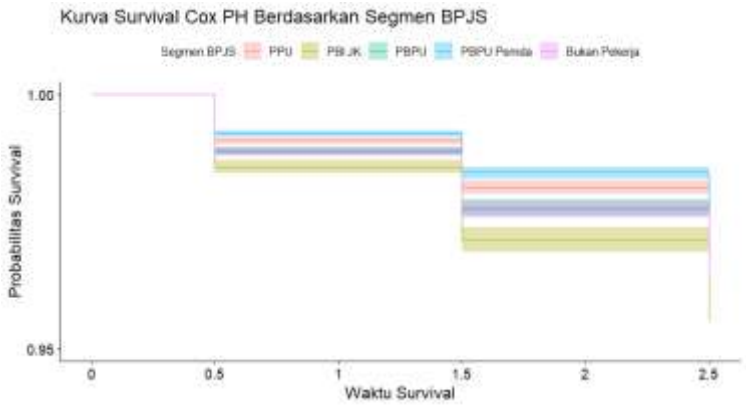

Figure 7. Cox PH Survival Curve by Segment

Source: Author's data processing (2026) using R software

The survival curve based on the Cox Poportional Hazard model shows that there is a difference in the probability of survival between BPJS membership segments. Throughout the observation period, the PPU segment tended to have a relatively higher probability of survival than other segments, while the PBI JK segment showed a lower probability of survival. The

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PBPU and Non-Worker segments are in a medium position, while the PBPU Local Government shows a relatively better pattern than some non-PPU segments.

Although the differences between the curves are not very wide, the consistent separation pattern indicates that the membership segment has an influence on patients' chances of survival. This reflects differences in socio-economic conditions, access to health services, and the quality of care between groups of participants.

These findings are in line with the results of Cox's regression which shows that some segments have a higher risk of death than the reference segment (PPU), thus reinforcing that the BPJS participation factor is an important determinant in the analysis of patient survival.

4. Covariate of Domicile

a. Domicile covariate 2 (Coefficient = 0.01)

Hazard Rate = . This means that by controlling for other covariates, individuals living in Domicile 2 had a 1.01 times greater risk of occurrence than individuals in Domicile 1 (reference category), but this result was not statistically significant.$e^{0,01} \approx 1,01$

b. Domicile covariate 3 (Coefficient = 0.08)

Hazard Rate = . This means that by controlling for other covariates, individuals living in Domicile 3 have a 1.08 times higher risk of occurrence compared to individuals in Domicile 1.$e^{0,08} \approx 1,08$

c. Domicile covariate 4 (Coefficient = 0.20)

Hazard Rate = . This means that by controlling for other covariates, individuals living in Domicile 4 have a 1.22 times higher risk of occurrence compared to individuals in Domicile 1.$e^{0,20} \approx 1,22$

d. Domicile covariate 5 (Coefficient = 0.22)

Hazard Rate = . This means that by controlling for other covariates, individuals living in Domicile 5 have a 1.25 times higher risk of occurrence compared to individuals in Domicile 1.$e^{0,22} \approx 1,25$

The following is a graph that illustrates the difference in survival probabilities between domicile groups.

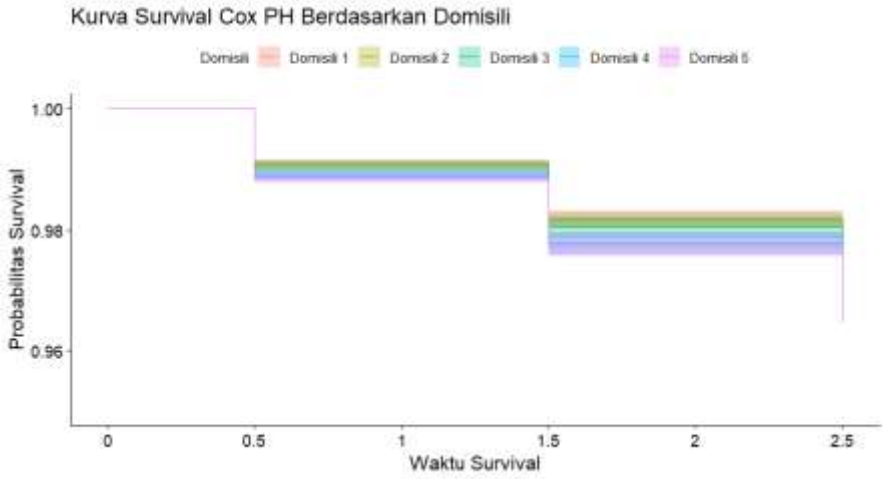

Figure 8. Survival curve by domicile group.

Source: Author's data processing (2026) using R software

The survival curve based on the Cox Proportional Hazard model shows that the difference in survival probability between the domicile groups is relatively small, but still shows a stable pattern throughout the observation period. In general, all domicile groups have a high probability of survival with less noticeable variations compared to other covariates such as age or membership segments.

However, there is a tendency that some domicile groups have a slightly lower probability of survival than reference groups (Domicile 1). This indicates that geographical factors still have an influence on the patient's chances of survival, albeit to a relatively moderate degree.

However, the results of the proportional hazards assumption test showed that the domicile variable did not meet these assumptions, indicating that the influence of domicile on hazard was not constant all the time. Thus, although the curve pattern appears to be relatively visually stable, statistically there is an indication of a time-dependent effect on the domicile variable.

Analysis Accelerated Failure Time

First of all, it is necessary to carry out a test first to find out which distribution is most suitable for doing calculations. As is known, the Accelerated Failure Time method is a parametric survival analysis, so an appropriate distribution is required.

Next, Model Tests will be carried out on four types of distributions, namely Weibull, Log-normal, Log-logistic, and Exponential.

The distribution to be selected is the one that produces the smallest Akaike Information Criterion (AIC) number.

The following are the results of the Model Test.

Table 6. Akaike Information Criterion Test Results

No	Distribution	Akaike Information Criterion (AIC)	Bayesian Information Criterion (BIC)	Log-Likelihood
1	Weibull	76.331	76.456	(38.152)
2	Log-logistic	76.468	76.593	(38.221)
3	Log-normal	76.569	76.694	(38.271)
4	Exponential	77.716	77.831	(38.846)

Source: Author's data processing (2026) using R software

It can be seen that the Weibull Distribution has the least AIC value compared to other distributions with an AIC value of 76,331. The analysis also considered the Bayesian Information Criterion (BIC) value. BIC is similar to AIC, but imposes a greater penalty on complex models, especially on large samples. The results of the model test also showed that Weibull Distribution had the smallest BIC value of 76,456. It also shows that despite considering the complexity penalty of the model, Weibull remains the most efficient and most suitable model.

Next is the interpretation of the Log-Likelihood value. The Weibull Distribution Log-Likelihood value is -38,152, the largest among other distributions. This is in accordance with the principle that the greater the Log-Likelihood (the closer it is to zero), the better the model.

Based on the results of the above test, it is concluded that the Weibull distribution is the most suitable distribution for Accelerated Failure Time (AFT) analysis.

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Subsequently, Accelerated Failure Time (AFT) analysis was carried out using the Weibull distribution. The results are as follows:

Table 7. Results of Accelerated Failure Time (AFT) analysis.

Variables	Value (β)	Std. Error	z	p-value	Time Ratio (exp β)	Time Reduction Effect (%)
(Intercept)	3,1665	0,0333	95,0275	<0.001	23,7234	
Ages 36–60	-0,9806	0,0234	-41,8424	<0.001	0,3751	62%
Age >60	-1,4120	0,0261	-54,0487	<0.001	0,2437	76%
Gender Women	0,2435	0,0145	16,8254	<0.001	1,2757	-28%
Non-Employee Segment	-0,1425	0,0242	-5,8851	<0.001	0,8672	13%
Segmen PBI JK	-0,0060	0,0204	-0,2926	0.770	0,9940	1%
PBPU Segment	0,2814	0,0239	11,7758	<0.001	1,3249	-32%
Segmen PBPU Local Government	0,1602	0,0191	8,3882	<0.001	1,1737	-17%
Domicile 2	-0,0057	0,0176	-0,3233	0.746	0,9943	1%
Domicile 3	-0,0480	0,0247	-1,9414	0.052	0,9531	5%
Domicile 4	-0,1339	0,0210	-6,3747	<0.001	0,8747	13%
Domicile 5	-0,1524	0,0229	-6,6517	<0.001	0,8586	14%

Source: Author's data processing (2026) using R software

Based on the model output, the Accelerated Failure Time (AFT) model is obtained as follows:

$T = exp(\beta_0 + \beta_1 X_1 ++\ldots+)\beta_2 X_2 \beta_k X_k$

T = exp (3.1665 – 0.9806 Age 36-60 – 1.4120 Age >60 + 0.2435 Female Gender – 0.1425 Non-Worker Segment – 0.0060 PBI JK Segment + 0.2814 PBPU Segment + 0.1602 Local Government PBPU Segment – 0.0057 Domicile 2 – 0.0480 Domicile 3 – 0.1339 Domicile 4 – 0.1524 Domicile 5.

The explanation of each variable is as follows:

The interpretation of the results of the analysis is as follows:

1. Age Covariate
   a. Age Group 36–60 years (Coefficient β = -0.9806)
      The 36–60-year-old age group has a Time Ratio (exp β) of 0.3751. This means that assuming other covariates are constant, TB patients aged 36–60 years have a survival time of about 62% shorter than those in the age group of 0–35 years. This result was statistically significant (p-value <0.001).
   b. Age Group >60 years (Coefficient β = -1.4120)
      The age group of >60 years has a Time Ratio of 0.2437. This means that assuming other covariates are constant, TB patients aged >60 years have a survival time of about 76% shorter than the age group of 0–35 years. This result was statistically significant (p-value <0.001).

2. Sex Covariates
    a. Female Sex (Coefficient β = 0.2435)
    Female TB patients have a Time Ratio of 1.2757. This means that assuming other covariates are constant, female TB patients have a survival time of about 28% longer than male patients. This result was statistically significant (p-value <0.001).
3. Membership Segment Covariates
    a. Non-Worker Segment (Coefficient β = -0.1425)
    Non-Worker segment participants have a Time Ratio of 0.8672. This means that assuming other covariates are constant, TB patients in the non-Worker segment have a survival time of about 13% shorter than the PPU segment. This result was statistically significant (p-value <0.001).
    b. PBI JK Segment (Coefficient β = -0.0060)
    Participants in the PBI JK segment have a Time Ratio of 0.9940. This means that assuming other covariates are constant, TB patients in the PBI JK segment have a survival time about 1% shorter than the PPU segment. However, this result was not statistically significant (p-value = 0.770).
    c. PBPU Segment (Coefficient β = 0.2814)
    Participants in the PBPU segment have a Time Ratio of 1.3249. This means that assuming other covariates are constant, TB patients in the PBPU segment have a survival time of about 32% longer than the PPU segment. This result was statistically significant (p-value <0.001).
    d. Local Government PBPU Segment (Coefficient β = 0.1602)
    Participants in the PBPU segment of the Regional Government have a Time Ratio of 1.1737. This means that assuming other covariates are constant, TB patients in the PBPU segment of the local government have a survival time of about 17% longer than the PPU segment. This result was statistically significant (p-value <0.001).
4. Covariate Domicile
    a. Domicile 2 (Coefficients β = -0.0057)
    TB patients in Domicile 2 have a Time Ratio of 0.9943. This means that assuming other covariates are constant, TB patients in Domicile 2 have a survival time about 1% shorter than Domicile 1. However, this result was not statistically significant (p-value = 0.746).
    b. Domicile 3 (Coefficients β = -0.0480)
    TB patients at Domicile 3 have a Time Ratio of 0.9531. This means that assuming other covariates are constant, TB patients in Domicile 3 have a survival time about 5% shorter than Domicile 1. However, this result was not statistically significant (p-value = 0.052).
    c. Domicile 4 (Coefficients β = -0.1339)
    TB patients in Domicile 4 have a Time Ratio of 0.8747. This means that assuming other covariates are constant, TB patients in Domicile 4 have a survival time about 13% shorter than Domicile 1. This result was statistically significant (p-value <0.001).
    d. Domicile 5 (Coefficients β = -0.1524)
    TB patients at Domicile 5 have a Time Ratio of 0.8586. This means that assuming other covariates are constant, TB patients in Domicile 5 have a survival time about 14% shorter than Domicile 1. This result was statistically significant (p-value <0.001).

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Comparison Model Cox Proportional Hazard dan Accelerated Failure Time

The results of the analysis showed that the Cox Proportional Hazards (Cox PH) and Accelerated Failure Time (AFT) models were both able to identify factors that affect the death time of tuberculosis patients participating in the National Health Insurance Program (JKN). Nevertheless, the two models have different approaches and interpretations in explaining the relationship between covariates and patient survival.

The Cox PH model is a semi-parametric survival model that focuses on estimating the hazard ratio, which is a change in the relative risk of death due to the influence of a covariate. In contrast, the AFT model is a parametric survival model that directly models survival time and produces estimates in the form of time ratios that describe the acceleration or slowdown of the time of death. Thus, Cox PH places more emphasis on changes in the level of risk of death, while AFT places more emphasis on changes in the duration of patient survival.

In this study, the age variable showed consistent results in both models. In the Cox PH model, the 36–60-year-old age group had a hazard ratio of 4.25, while the >60-year-old age group had a hazard ratio of 8.09 compared to the 0–35-year-old age group. These results show that the higher the age of the patient, the greater the risk of death from tuberculosis. The same findings were also obtained in the AFT model, where the age group of 36–60 years had a time ratio of 0.3751 and the age group of >60 years of age of 0.2437. This indicates that older patients have a significantly shorter survival time than younger age groups. The consistency of the direction of influence in both models showed that age was a major determinant factor in the survival of tuberculosis patients.

The gender variable also showed relatively consistent results between models. In the Cox PH model, female patients had a hazard ratio of 0.70 compared to men, which means that women had a lower risk of death. These results are strengthened by the AFT model which shows that female patients have a time ratio of 1.2757 or a survival time of about 28% longer than men. These findings suggest that females tend to have a better survival prognosis than males.

In the variables of the membership segment, the two models also show a parallel pattern. The Cox PH model shows that the PBI JK, PBPU, and Non-Worker segments have higher hazards than the PPU segment, while the local government PBPU has a lower hazard. In the AFT model, the Non-Worker and PBI JK segments showed a shorter survival time compared to PPU, while the PBPU and PBPU segments of the Regional Government had a longer survival time. These results show that socioeconomic factors and access to health services have the potential to affect survival outcomes of tuberculosis patients.

Furthermore, the domicile variable showed that some regions had a higher risk of mortality and a shorter survival time than the reference region. In the Cox PH model, Domicile 4 and Domicile 5 have hazard ratios of 1.22 and 1.25, respectively. Relatively consistent results were also obtained in the AFT model, where Domicile 4 and Domicile 5 had a time ratio of 0.8747 and 0.8586 respectively, which showed a shorter survival time than Domicile 1. These findings indicate geographical disparities in access to health services and the quality of tuberculosis treatment between regions.

Although both models produce relatively consistent directions of influence, there are fundamental differences in the model's assumptions. The Cox PH model requires proportional hazards assumption, i.e. the hazard ratio between groups must be constant all the time. The

results of the residual Schoenfeld test in this study showed that several covariates such as age, membership segment, and domicile did not meet the assumption of proportional hazards. This condition causes the interpretation of the Cox PH model to need to be done carefully because there are indications that the influence of some covariate's changes over time.

In contrast, the AFT model does not require the assumption of proportional hazards and focuses more on direct estimates of survival time. Therefore, the AFT model is a relevant alternative in this study, especially since the main objective of the study is to analyze the time to death of tuberculosis patients. In addition, the Weibull AFT model also showed the best performance based on the results of the model evaluation using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood. The Weibull distribution yielded an AIC value of 76,330.99, a BIC value of 76,456.12, and a Log-Likelihood value of -38,152.49, which is better than the Exponential, Log-normal, and Log-logistic distributions. These results show that the Weibull distribution is the most appropriate parametric distribution to describe the survival pattern of tuberculosis patients in this study.

In general, the Cox PH model has the advantage that it does not require certain survival distribution assumptions and is more popular in medical research. However, this model has limitations when the assumption of proportional hazards is not met. On the other hand, the AFT model has the advantage of providing a more intuitive interpretation of the duration of survival and is more suitable for research that focuses on accelerating or slowing down the timing of events. However, the AFT model is sensitive to the selection of the parametric distribution used.

Based on the overall results of the study, the Cox PH and AFT models can be used complementarily in the survival analysis of tuberculosis patients. The Cox PH model is more suitable to be used to identify relative risk factors for death, while the AFT model is more suitable to be used to measure changes in the duration of patient survival. In the context of this study, the Weibull AFT model is considered more relevant because it is able to provide a direct interpretation of the time to death of tuberculosis patients and does not rely on the assumption of proportional hazards that are not fully fulfilled in the Cox PH model.

CONCLUSION

Based on the results of the analysis of the survival of tuberculosis patients participating in JKN in 2015–2024 using the Kaplan-Meier method, Cox Proportional Hazards, and Accelerated Failure Time (AFT), it was found that age, gender, membership segment, and domicile had a significant effect on the survival time of patients. Elderly patients, PBI JK participants, and patients living in certain areas have a higher risk of death and a shorter survival time. The AFT Weibull model was chosen as the best model because it provides results that are more in line with the characteristics of the data and are able to interpret the duration of survival directly. These findings point to the importance of improving health services and more targeted interventions for high-risk groups to reduce tuberculosis deaths. Based on these findings, several recommendations are proposed. For the Ministry of Health, the significant effect of age on survival time suggests the need for age-specific TB screening and treatment protocols, particularly for elderly patients who face the highest mortality risk, including geriatric-friendly service models and integrated management of comorbidities. For BPJS Kesehatan, the higher mortality risk among PBI JK participants indicates the necessity of

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strengthening access to quality health services for economically vulnerable groups, including improved referral pathways, reduced service barriers, and enhanced monitoring of treatment adherence in this segment. For healthcare facilities, the geographic disparities in survival outcomes highlight the importance of equitable distribution of TB diagnostic and treatment resources across regions, with particular attention to areas with shorter survival times, as well as strengthening primary healthcare capacity for early detection and comprehensive case management. For future research, this study recommends further investigation incorporating additional clinical variables such as HIV coinfection, diabetes mellitus, multidrug-resistant TB status, and treatment adherence, as well as extending the observation period to capture longer-term survival patterns. Additionally, future studies could explore the application of machine learning approaches to survival analysis and conduct comparative studies across different provinces to better understand regional variations in TB outcomes.

REFERENCE

Carter et al. 2021. Survival analysis of patients with tuberculosis and risk factors for multidrug-resistant tuberculosis in Monrovia, Liberia. Plos One: Monrovia.

Crowther et al. 2020. A flexible parametric accelerated failure time model. Leicester: Arxiv.

Daniel. Thomas M. 2006. The history of tuberculosis. Cleveland: Elsevier.

David G. Kleinbaum & Mitchel Klein. 2020. Survival Analysis: A Self-Learning Text. Atlanta: Springer.

Davidson. George et all. 2024. Overview of Tuberculosis: Causes. Symptoms and Risk Factors. West Bengal: Asian Journal of Research in Infectious Diseases

Fuady. Ahmad. 2019. Catastrophic Total Costs in Tuberculosis-Affected Households and Their Determinants Since Indonesia's Implementation of Universal Health Coverage. Jakarta: Mednexus

GBD 2019 Tuberculosis Collaborators. 2022. Global. regional. and national sex differences in the global burden of tuberculosis by HIV status. 1990–2019: results from the Global Burden of Disease Study 2019. Seattle: The Lancet Infectious Diseases

Global Tuberkulosis Report. 2024. Global Tuberculosis Report. Jakarta: World Health Organization.

Jeon. Christie Y & Murray. Megan B. 2008. Diabetes Mellitus Increases the Risk of Active Tuberculosis: A Systematic Review of 13 Observational Studies. Massachusetts: Plos Medicine.

Kemenkes. 2024. Laporan Hasil Studi Inventori TB Indonesia 2023 – 2024. Jakarta: Kementerian Kesehatan RI.

Lee. Elisa T & Wang. John Wenyu. 2003. Statistical Methods for Survival Data Analysis. New Jersey: Willey.

Liu. Kui. 2022. Survival Analysis and Associated Factors for Pulmonary Tuberculosis Death: Evidence from the Information System of Tuberculosis Disease and Mortality Surveillance in China. Zhejiang: Taylor & Francis.

Pangaribuan. Lamria. 2020. Faktor-Faktor Yang Mempengaruhi Kejadian Tuberkulosis Pada Umur 15 Tahun Ke Atas Di Indonesia (Analisis Data Survei Prevalensi Tuberkulosis (SPTB) Di Indonesia 2013-2014). Jakarta: 2020.

Pralambang. Sesar Dayu and Setiawan. Sona (2021) "Faktor Risiko Kejadian Tuberkulosis di Indonesia." Jurnal Biostatistik. Kependudukan. dan Informatika Kesehatan: Vol. 2: No. 1. Article 5.

Sukardi. 2018. Metodologi Penelitian Pendidikan Kompetensi dan Praktiknya. Jakarta: Bumi Aksara.

Swindell, William R. 2009. Accelerated failure time models provide a useful statistical framework for aging research.

Tanimura. Tadayuki. 2014. Financial Burden for Tuberculosis Patients In Low- and Middle-Income Countries: A Systematic Review. United Kingdom: European Respiratory Journal.

Vélez- Gómez. Diego. 2025. Survival and factors associated with mortality among people with tuberculosis in Medellín. Colombia (2018–2023): a retrospective cohort study. Medellín: BMJ Group.