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Mortality Risk Factors Among Indonesians with Tuberculosis: An Analysis of a National Health Insurance Data

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Abstract

Tuberculosis (TB) significantly contributes to global mortality; thus, identifying mortality risks is crucial for effective disease management. This study aims to explore the risks of mortality among Indonesians with TB. This case-control study analyzed Indonesian health insurance data (2015-2022), employing propensity score matching (1:4 ratio) and Cox modeling to assess the relationship between mortality and demographics/comorbidities. Mortality was treated as a binary (death or survived) and a multistate outcome (including death within two months, death afterward, and survived). The analysis included 60,472 subjects and 1,777 deaths, revealing that most demographics had no correlation with mortality, except for marital status. Being married was protective against mortality after two months (Hazard Ratio [HR] 0.65, 95% Confidence Interval [CI]: 0.45-0.93). Anemia increased mortality risk over time (HR 3.62 within the first two months; 9.19 thereafter). Cancer and heart failure heightened mortality risk early on, while HIV affected later stages. Interestingly, some chronic conditions may provide protective effects. Access to healthcare through universal health coverage (UHC) may help reduce mortality risks. The study emphasizes critical management periods for TB in patients with specific conditions and highlights the importance of UHC in mitigating sociodemographic disparities to improve health outcomes.

INTRODUCTION

Tuberculosis (TB) is the leading cause of death due to a single infectious agent (World Health Organization, 2025). The global commitment is to end the TB epidemic by 2030, and the End TB Strategy was declared in 2015 (World Health Organization, n.d.). The strategy aims to reduce new TB cases by 80%, TB-related deaths by 90%, and eliminate any household catastrophic costs due to TB by 2030 (World Health Organization, n.d.). However, the strategy's progress has been disrupted, partly due to the COVID-19 pandemic (Surendra et al., 2023; World Health Organization, n.d.), resulting in only a 19% net reduction of deaths in 2022, far from the targeted 75% reduction by 2025 (World Health Organization, 2025). Risk factors for TB mortality have been studied (Birlie et al., 2015; Chu et al., 2019; Chung et al., 2021; Crabtree-Ramirez et al., 2022; Kim et al., 2016; Min et al., 2019; Nacarapa et al., 2022; Osei et al., 2020; Osman et al., 2021), which can be classified into demographic and clinical risk factors. Age, sex, marital status, and lifestyle, along with clinical factors such as dia-

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betes mellitus (DM), human immunodeficiency virus (HIV) infection, malignancy, anemia, and cardiovascular diseases, showed varying associations with mortality (Birlie et al., 2015; Chu et al., 2019; Chung et al., 2021; Crabtree-Ramirez et al., 2022; Kim et al., 2016; Min et al., 2019; Nacarapa et al., 2022; Osei et al., 2020; Osman et al., 2021).

Indonesia has one of the highest TB burdens in the world, ranking second globally (World Health Organization, 2025). While some risk factors for mortality have been studied, differences in the national context—such as the prevalence of HIV (Min et al., 2019)—may lead to distinct risk factors. This underscores the necessity to investigate the specific risk factors linked to TB mortality in Indonesia, as this can enhance and accelerate national and global efforts to end TB. Most studies on TB in Indonesia rely on localized data, such as a study in a hospital (Elhidsi et al., 2021), or only conducted in several cities/regencies (Fuady et al., 2020). Nationwide studies in Indonesia mainly used data from the TB notification system (Iskandar et al., 2023; Surendra et al., 2023). Another study used a cross-sectional design to screen nationwide TB prevalence (Noviyani et al., 2021). Some limitations of those studies were noted, such as lack of generalizability due to limited coverage of study subjects (Elhidsi et al., 2021; Fuady et al., 2020), focusing only on TB-related conditions (Iskandar et al., 2023; Surendra et al., 2023), or lack of longitudinal feature (Noviyani et al., 2021), which may lead to a loss of information regarding the dynamic treatment process over time.

Indonesia has been implementing universal health coverage (UHC) since 2014 through the *Badan Penyelenggara Jaminan Sosial Kesehatan* (*BPJS Kesehatan,* or BPJS), a governmental agency that administers healthcare services insurance (Ng et al., 2019). The UHC currently covers almost 98% of the Indonesian population. The BPJS has been collecting vast healthcare services data since its inception. In 2019, BPJS launched its first data sample, which has been regularly updated since (Ariawan et al., 2022). BPJS also released specific datasets, such as Diabetes Mellitus and TB datasets. The first TB dataset was launched at the end of 2022 (Ariawan et al., 2022). This dataset offers a unique approach compared to the Indonesian Tuberculosis register, as it also includes information on non-TB healthcare services. The data is longitudinal, allowing for differentiation of mortality risk factors during the first two months and thereafter. Exploring early death, which occurs within two months, is crucial since it is often understudied (Min et al., 2019).

We aim to analyze the TB dataset to: 1) define the association of demographics and comorbidities with TB-related deaths, and 2) differentiate the mortality risk factors during and after two months of treatment. We conducted a case-control study using time-varying Cox modelling to answer these questions, utilizing data from BPJS services. This study can provide insights into TB mortality risks and the critical periods for these risks, allowing for the development of targeted TB management strategies through allocating specific resources, improving patient outcomes, and ultimately reducing the overall burden of tuberculosis in affected populations.

METHOD

Data source

The dataset contains information on almost 100,000 patients diagnosed with TB during a visit in 2019 (Ariawan et al., 2022). An additional dataset was launched in 2023, adding about 13,000 patients to the initial cohort. The healthcare services accessed by this cohort were not limited to TB treatment and spanned from 2015 to 2022.

The BPJS data sample is divided into several subsets (Ariawan et al., 2022). Each subset has unique identifiers that allow linkage to others. The diagnoses were mapped to the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) 2010 version codes.

Study design

We employed a case-control design in our study. We considered any death recorded in the discharge report during a TB visit as a case. We selected individuals who survived until their last TB visit to form the control group. We then matched them to the case group in a 1:4 ratio. Since we used administrative data, this study complies with the RECORD statement (Benchimol et al., 2015).

TB case selection process

Administrative data is often not created for research purposes, which can sometimes lead to unreliable validity. Therefore, we implemented several measures to ensure that the data accurately reflects TB treatment in Indonesia.

The first measure was to define healthcare visits. The number of visits for each participant varied; some had only one visit per month, while others may have had multiple visits for the same diagnosis in a month. Since BPJS services for

chronic diseases, particularly the provision of medicines, are regulated on a 30-day basis, we standardized visits into monthly occurrences. This means that at least one visit for a particular diagnosis in a month is required. A TB visit was defined as having a TB diagnosis (ICD-10 codes A15-19) made in secondary care facilities during that month. If there was no secondary care visit in that month, we used the diagnosis made in primary care facilities instead. The second measure involves identifying TB cases. To be included in the analysis, an individual must have at least two consecutive months of TB visits, defined as having two visits with a maximum gap of two months between them. We excluded cases that consisted only of promotive or preventive visits, inaccurately recorded death and age data, and inpatient visits that were part of other inpatient visits. Additionally, we excluded TB diagnoses made in primary care without corresponding diagnoses in secondary care visits. Most of these exclusion criteria were implemented to prevent fraudulent claims, ensure complete TB treatment, and confirm TB diagnoses. Details on the exclusion criteria can be found in Figure 1.

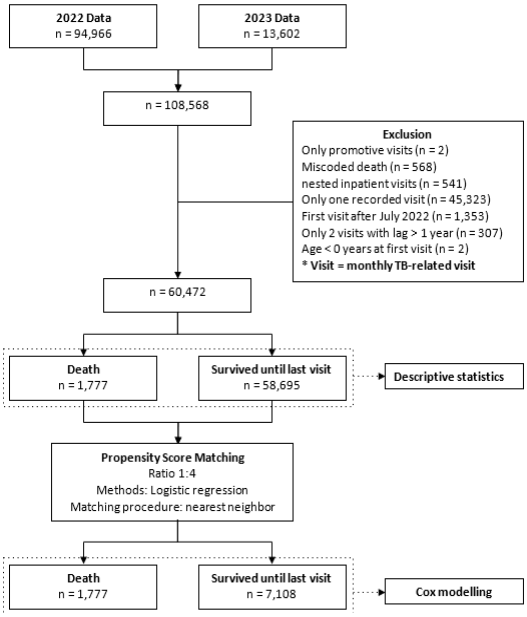

Figure 1. Case and controls selection process

For the matching process, we determined the propensity score based on demographics and clinical characteristics at the first TB visit. We conducted the matching using logistic regression with the nearest neighbor method and found that the optimal model was a logistic model with a ratio of 1:4 without replacement.

Variables of interest

Independent variables analyzed in this study include demographics such as sex, age, marital status, beneficiary type, class, and comorbidities. Age was calculated in years based on the month of the first TB visit and the month of birth. Marital status was classified as unmarried, married, and divorced/widowed. The beneficiary type was defined as a subsidized and non-subsidized beneficiary. Beneficiaries whose premiums were paid by the government were categorized as subsidized, while others were categorized as non-subsidized beneficiaries. Class reflects the insurance class system, which is based on the monthly premium paid, with the first class being the highest tier. Higher-paying classes provide better amenities during inpatient care, such as specific appliances in the room and fewer patients per room. However, healthcare-related services and outpatient services are similar across all classes. Subsidized beneficiaries are assigned to the third class, while non-subsidized beneficiaries can choose their preferred class based on the premium they or their employers pay. We selected chronic comorbidities based on their high mortality risk (i.e., cancer and HIV infection) or their high prevalence in the cohorts (e.g., DM, asthma, bronchitis, osteoarthritis, dorsopathies, anemia, heart failure, hypertension, and dyslipidemia). We categorized the comorbidities using their corresponding ICD-10 codes. Similar to the definition of TB cases, we define comorbidities as instances where an individual has at least two consecutive visits for those conditions.

Descriptive statistics

Since BPJS uses stratified random sampling, the likelihood of beneficiaries being selected differs among them. Therefore, the data sample includes a weighting variable to account for these differences in probability (Ariawan et al., 2022). We incorporated the weighting variable into our analysis and reported both unweighted and weighted results.

We calculated the cumulative number and percentage of deaths and censored events that occurred during the first 12 months. Additionally, we determined the proportion of patients with comorbidities during their TB treatment.

To evaluate the effectiveness of the matching process, we analyzed the baseline characteristics of case and control cohorts, focusing on the variables present during the first TB visit. We compared these characteristics using both matched and unmatched data. For continuous variables, we calculated various statistics and

conducted appropriate statistical tests, such as the mean, standard deviation, and the p-value of Student's t-test or its non-parametric counterpart. For categorical variables, we calculated the proportion of each category and used Pearson's chi-squared test for comparison. All calculations were based on weighted data.

Cox modelling

We employed a time-varying Cox model to assess the mortality risk for each demographic and comorbidity. When analyzing a binary outcome, such as death or survival, the Cox model offers greater statistical power than logistic regression. Furthermore, if the number of survivors is similar across the factors being analyzed at the end of the observation period, the Cox model can still detect differences in mortality rates between categories. This capability allows the Cox model to identify scenarios where one group experiences a faster rate of mortality than another, a distinction that logistic regression may not capture effectively (George et al., 2014). In the model, the time-fixed variables include sex and age at the first TB visit. The time-varying variables include marital status, beneficiary type, class, TB type, and comorbidities. We conducted a univariate analysis for each variable. For multivariate analysis, we included all variables in the model. We calculated the hazard ratio (HR), 95% confidence interval (95% CI), and p-value, with an alpha level of < 0.05 for significance. We also utilized a multi-state Cox model to evaluate time-varying hazards. The mortality status was classified as no/censored, death in two-month visits, and death in more than two-month visits in this multi-state model.

Software and related packages

We used R 4.5.1 (R Core Team; Vienna, Austria) (R Core Team, 2023) for data preprocessing and statistical analyses. We utilized packages such as *tidyverse* (Wickham et al., 2019) and *zoo* (Zeileis & Grothendieck, 2005) for data preprocessing, *survey* (Lumley, 2004) and *MatchIt* (Ho et al., 2011) for the matching process, *tableone* (Yoshida & Bartel, 2022) to compare characteristics between patients who died and survived, and *survival* (Thernau & Grambsch, 2000) for Cox modeling.

Ethical Clearance Letter

The protocol was approved by the ethics committee of the Health Polytechnic of Jambi, Ministry of Health, Republic of Indonesia (No. LB.02.06/2/01/2024)

RESULT AND DISCUSSION

Of the initial cohorts, 41.8% (n = 45,323) were excluded because they had only one recorded visit (Figure 1). The total number of deaths was 1,777 (n weighted = 15,192.4), which comprised approximately 3% of the total patients in both weighted and unweighted data. More than 30% of deaths occurred within two months, and almost two-thirds of deaths occurred within the first year of visit (Table 1). The top five comorbidities were DM, hypertension, chronic obstructive pulmonary disease (COPD), asthma, and dorsopathies (Table 2).

Table 1. Cumulative numbers of deaths & censored events within 12 months after the first visit

Month	Unweighted data		Weighted data	
	Death	Censored	Death	Censored
	n (%)	n (%)	n (%)	n (%)
Month 2	629 (35.4)	6,654 (11.0)	4,706.3 (31.0)	47,825.3 (9.4)
Month 3	797 (44.9)	10,044 (16.6)	5,809.3 (38.2)	70,826.9 (13.9)
Month 4	918 (51.7)	13,198 (21.8)	6,740.2 (44.4)	96,925.1 (19.0)
Month 5	996 (56.0)	16,626 (27.5)	7,539.1 (49.6)	122,939.1 (24.1)
Month 6	1,057 (59.5)	21,721 (35.9)	7,804.9 (51.4)	166,016.3 (32.6)
Month 7	1,105 (62.2)	27,857 (46.1)	8,119.8 (53.4)	220,676.0 (43.3)
Month 8	1,143 (64.3)	31,530 (52.1)	8,436.4 (55.5)	253,056.2 (49.6)
Month 9	1,178 (66.3)	34,590 (57.2)	8,758.3 (57.6)	280,555.2 (55.0)
Month 10	1,211 (68.1)	37,672 (62.3)	9,341.0 (61.5)	305,696.6 (59.9)
Month 11	1,238 (69.7)	39,757 (65.7)	9,537.4 (62.8)	324,725.4 (63.7)
Month 12	1,266 (71.2)	41,398 (68.5)	9,724.2 (64.0)	337,539.2 (66.2)

The percentage of deaths was calculated from all deaths (n unweighted = 1,777, n weighted = 15,192.4); the percentage of censored events was calculated from total subjects at risk (n unweighted = 60,472, n weighted = 509,987.2)

Table 2. Comorbidities among subjects with tuberculosis

Comorbidity	ICD-10 Code	Unweighted data		Weighted data	
		≥ 1 visit	≥2 visits	≥1 visit	≥2 visits
		n (%)	n (%)	n (%)	n (%)
Cancer	C00 - C97	1,616 (2.7)	567 (0.9)	10,685.4 (2.1)	3,843.4 (0.8)
HIV	B20 - B24	1,421 (2.3)	1,010 (1.7)	10,269.4 (2.0)	7,932.2 (1.6)
Diabetes mellitus	E10 - E14	6,870 (11.4)	4,887 (8.1)	75,446.7 (14.8)	55,683.2 (10.9)
Asthma	J45	3,428 (5.7)	1,325 (2.2)	37,781.1 (7.4)	17,386.4 (3.4)
Bronchitis	J40 - J42	4,661 (7.7)	1,379 (2.3)	50,435.3 (9.9)	13,948.2 (2.7)
COPD	J44	5,880 (9.7)	2,997 (5.0)	63,577.0 (12.5)	34,262.5 (6.7)
Osteoarthritis	M15 - M19	2,150 (3.6)	808 (1.3)	21,601.6 (4.2)	8,590.2 (1.7)
Dorsopathies	M40 - M54	4,864 (8.0)	3,077 (5.1)	32,137.4 (6.3)	17,109.6 (3.4)
Hyperuricemia & gout	E79 & M10	1,761 (2.9)	614 (1.0)	12,465.3 (2.4)	4,113.4 (0.8)
Anemia	D63 - D64	4,324 (7.2)	1,771 (2.9)	34,319.0 (6.7)	14,267.9 (2.8)
Heart failure	I50	2,257 (3.7)	1,150 (1.9)	25,592.9 (5.0)	14,209.7 (2.8)
Hypertension	I10 - I15	6,888 (11.4)	3,665 (6.1)	68,970.6 (13.5)	39,049.6 (7.7)
Dyslipidemia	E78	1,135 (1.9)	389 (0.6)	9,759.7 (1.9)	3,135.0 (0.6)
Coronary artery disease	I25	1,590 (2.6)	749 (1.2)	19,677.6 (3.9)	10,433.1 (2.0)

ICD-10 = The International Statistical Classification of Diseases and Related Health Problems, 10th Edition, TB = Tuberculosis, HIV = Human immunodeficiency virus, COPD = Chronic obstructive pulmonary disease. The dataset used is the unmatched data. The percentage of comorbidities was calculated from the total subjects at risk (unweighted number of cases = 60,472, weighted number of cases = 509,987.2)

When comparing the baseline characteristics of case and control cohorts, we observed a statistically significant difference in sex, age, marital status, TB type, cancer, DM, COPD, hyperuricemia and gout, anemia, heart failure, hypertension, and coronary artery disease in the unmatched data. However, in the matched data, no statistically significant differences were observed (Table 3).

In the Cox model (Table 4), most demographic variables showed a non-statistically significant risk, except for marital status in unadjusted, adjusted, or multistate models. Married patients had a protective effect on mortality compared to unmarried patients (HR 0.65, 95% CI 0.45-0.93). DM, asthma, dorsopathies, hyperuricemia and gout, hypertension, and dyslipidemia did not exert any significant mortality risk. Anemia and osteoarthritis had significant associations over time. The risk of mortality increased with anemia, and the risk seemed to increase over time (2-month risk: HR 3.62, 95% CI 2.18-6.01 vs. >2-month risk: HR 9.19, 95% CI 5.80-14.54), while osteoarthritis showed protective effects to mortality with decreasing effect size over time (2-month risk: HR 0.06, 95% CI 0.02-0.23 vs. >2-month risk: HR 0.11, 95% CI 0.02-0.83). Comorbidities that were associated with mortality in the first two-month period but not after include cancer and heart failure (increased risks), bronchitis, COPD, and coronary artery disease (decreased risks). In contrast, HIV infection showed an increased risk of mortality after two months.

This study examines the risk factors for mortality among Indonesians with tuberculosis by analyzing data from the national healthcare insurance system. We observed no significant association between demographics and mortality except for marital status. We found no correlation between gender or age and mortality. However, a study from South Korea (Chung et al., 2021) reported that the percentage of male deaths was higher than that of female deaths, and the rate of deaths among individuals over the age of 75 was higher than that among younger individuals. This difference could be attributed to the nature of the data source used in the Korean study, which covers individuals who were not hospitalized or did not receive TB care (Chung et al., 2021). Notably, 16% of TB-related deaths in this study occurred outside of the hospital setting, indicating a significant proportion of individuals who did not seek care for TB (Chung et al., 2021). Due to data availability limitations, we could not determine the mortality status of individuals who did not seek TB care in our study. It is possible that a number of Indonesian males did not pursue TB treatment and may have died outside of the care system.

Our research further revealed that the be-

neficiary type and class, which can be considered as a proxy for socio-economic status, did not differ in mortality risks. TB is a chronic disease that can result in a significant financial burden, which can hinder access to proper healthcare (Gamtesa et al., 2020; Zimmerman et al., 2022). Therefore, our findings suggest that implementing UHC in Indonesia has successfully alleviated financial constraints and improved access to healthcare for TB patients from all socio-economic backgrounds.

Table 3. Subjects' characteristics at first tuberculosis visit stratified by mortality status

Variable	Unmatched data			Matched data		
	Mortality			Mortality		
	Yes	No	p	Yes	No	p
Unweighted n, %	1,777 (2.9)	58,695 (97.1)		1,777 (20.0)	7,108 (80.0)	
Weighted n, %	15,192.4 (3.0)	494,794.8 (97.0)		15,192.4 (20.1)	60,575.4 (79.9)	
Sex, %			0.037			0.954
Female	5,860.1 (38.6)	219,834.4 (44.4)		5,860.1 (38.6)	23,472.5 (38.7)	
Male	9,332.2 (61.4)	274,960.4 (55.6)		9,332.2 (61.4)	37,102.8 (61.3)	
Age, mean (SD)	49.58 (18.43)	36.72 (21.85)	<0.001	49.58 (18.43)	49.43 (19.22)	0.897
Marital status, %			<0.001			0.485
Unmarried	3,600.0 (23.7)	199,584.0 (40.3)		3,600.0 (23.7)	13,886.5 (22.9)	
Married	10,452.6 (68.8)	274,493.1 (55.5)		10,452.6 (68.8)	43,111.2 (71.2)	
Divorced	1,139.7 (7.5)	20,717.7 (4.2)		1,139.7 (7.5)	3,577.7 (5.9)	
Beneficiary type, %			0.063			0.213
Not Subsidized	8,392.4 (55.2)	299,237.0 (60.5)		8,392.4 (55.2)	31,086.4 (51.3)	
Subsidized	6,799.9 (44.8)	195,557.8 (39.5)		6,799.9 (44.8)	29,488.9 (48.7)	
Class, %			0.073			0.626
Class 1	2,717.0 (17.9)	84,753.5 (17.1)		2,717.0 (17.9)	10,728.1 (17.7)	
Class 2	2,731.7 (18.0)	116,150.3 (23.5)		2,731.7 (18.0)	9,608.6 (15.9)	
Class 3	9,743.7 (64.1)	293,891.0 (59.4)		9,743.7 (64.1)	40,238.7 (66.4)	
TB type, %			0.001			0.599
Pulmonary	13,535.1 (89.1)	420,940.9 (85.1)		13,535.1 (89.1)	54,564.7 (90.1)	
Extrapulmonary	1,393.8 (9.2)	59,762.9 (12.1)		1,393.8 (9.2)	5,069.1 (8.4)	
Both	263.5 (1.7)	14,090.9 (2.8)		263.5 (1.7)	941.5 (1.6)	
Cancer, %			<0.001			0.416
No	14,843.6 (97.7)	491,858.2 (99.4)		14,843.6 (97.7)	59,543.7 (98.3)	
Yes	348.8 (2.3)	2,936.6 (0.6)		348.8 (2.3)	1,031.7 (1.7)	
HIV, %			0.104			0.741
No	14,829.7 (97.6)	489,613.1 (99.0)		14,829.7 (97.6)	59,367.7 (98.0)	
Yes	362.7 (2.4)	5,181.7 (1.0)		362.7 (2.4)	1,207.7 (2.0)	
Diabetes mellitus, %			<0.001			0.429
No	12,812.4 (84.3)	453,318.1 (91.6)		12,812.4 (84.3)	52,139.4 (86.1)	
Yes	2,380.0 (15.7)	41,476.7 (8.4)		2,380.0 (15.7)	8,435.9 (13.9)	

Variable	Unmatched data			Matched data		
	Mortality			Mortality		
	Yes	No	p	Yes	No	p
Asthma, %			0.745			0.437
No	14,893.3 (98.0)	485,966.7 (98.2)		14,893.3 (98.0)	59,664.2 (98.5)	
Yes	299.0 (2.0)	8,828.1 (1.8)		299.0 (2.0)	911.2 (1.5)	
Bronchitis, %			0.117			0.261
No	14,864.6 (97.8)	478,503.6 (96.7)		14,864.6 (97.8)	58,627.2 (96.8)	
Yes	327.7 (2.2)	16,291.3 (3.3)		327.7 (2.2)	1,948.1 (3.2)	
COPD, %			0.01			0.856
No	14,323.8 (94.3)	477,125.3 (96.4)		14,323.8 (94.3)	57,239.8 (94.5)	
Yes	868.6 (5.7)	17,669.6 (3.6)		868.6 (5.7)	3,335.5 (5.5)	
Osteoarthritis, %			0.099			0.187
No	15,157.4 (99.8)	492,207.1 (99.5)		15,157.4 (99.8)	60,509.2 (99.9)	
Yes	35.0 (0.2)	2,587.8 (0.5)		35.0 (0.2)	66.1 (0.1)	
Dorsopathies, %			0.341			0.455
No	14,954.3 (98.4)	485,003.0 (98.0)		14,954.3 (98.4)	59,800.7 (98.7)	
Yes	238.1 (1.6)	9,791.8 (2.0)		238.1 (1.6)	774.7 (1.3)	
Hyperuricemia & gout, %			<0.001			0.461
No	15,022.7 (98.9)	493,140.0 (99.7)		15,022.7 (98.9)	60,049.7 (99.1)	
Yes	169.7 (1.1)	1,654.8 (0.3)		169.7 (1.1)	525.7 (0.9)	
Anemia, %			<0.001			0.108
No	13,615.0 (89.6)	479,829.3 (97.0)		13,615.0 (89.6)	55,956.0 (92.4)	
Yes	1,577.4 (10.4)	14,965.5 (3.0)		1,577.4 (10.4)	4,619.4 (7.6)	
Heart failure, %			0.001			0.637
No	14,466.6 (95.2)	486,639.6 (98.4)		14,466.6 (95.2)	58,106.1 (95.9)	
Yes	725.8 (4.8)	8,155.2 (1.6)		725.8 (4.8)	2,469.3 (4.1)	
Hypertension, %			<0.001			0.88
No	14,020.6 (92.3)	475,010.4 (96.0)		14,020.6 (92.3)	56,048.8 (92.5)	
Yes	1,171.7 (7.7)	19,784.4 (4.0)		1,171.7 (7.7)	4,526.6 (7.5)	
Dyslipidemia, %			0.506			0.667
No	15,137.3 (99.6)	493,454.6 (99.7)		15,137.3 (99.6)	60,281.1 (99.5)	
Yes	55.1 (0.4)	1,340.2 (0.3)		55.1 (0.4)	294.2 (0.5)	
Coronary artery disease, %			0.001			0.901
No	14,752.9 (97.1)	490,130.0 (99.1)		14,752.9 (97.1)	58,737.7 (97.0)	
Yes	439.4 (2.9)	4,664.8 (0.9)		439.4 (2.9)	1,837.7 (3.0)	

Unweighted n = unweighted number of cases, weighted n = weighted number of cases. The weight is calculated based on the probability of cases being included in the BPJS sample data given its use of stratified random sampling.

Table 4. Risks of mortality based on demographics and comorbidities

Variables	Unadjusted model		Adjusted model		Adjusted multi-state model			
			Mortality in 2 months		Mortality > 2 months			
	HR (95% CI)	p	HR (95% CI)	p	HR (95% CI)	p	HR (95% CI)	p
Sex (Reference: Female)								
Male	1.02 (0.82 - 1.27)	0.857	1.10 (0.87 - 1.40)	0.428	1.08 (0.69 - 1.70)	0.734	1.09 (0.83 - 1.44)	0.522
Age	1.00 (0.99 - 1.00)	0.506	1.00 (1.00 - 1.01)	0.286	1.00 (0.99 - 1.02)	0.652	1.00 (1.00 - 1.01)	0.340
Marital status (Reference: Unmarried)								
Married	0.80 (0.61 - 1.05)	0.103	0.81 (0.59 - 1.12)	0.209	1.30 (0.66 - 2.53)	0.447	0.65 (0.45 - 0.93)	0.019
Divorced	1.00 (0.65 - 1.53)	0.991	0.69 (0.36 - 1.32)	0.264	1.59 (0.57 - 4.47)	0.378	0.44 (0.20 - 1.00)	0.051
Beneficiary type (Reference: Not subsidized)								
Subsidized	0.90 (0.72 - 1.12)	0.350	0.83 (0.62 - 1.10)	0.185	0.85 (0.48 - 1.52)	0.585	0.81 (0.59 - 1.11)	0.187
Class (Ref: Class 1)								
Class 2	1.13 (0.78 - 1.63)	0.530	1.19 (0.83 - 1.70)	0.343	1.07 (0.52 - 2.22)	0.857	1.23 (0.82 - 1.84)	0.314
Class 3	1.05 (0.80 - 1.37)	0.725	1.23 (0.90 - 1.69)	0.201	1.16 (0.61 - 2.21)	0.644	1.26 (0.88 - 1.81)	0.211
TB type (Reference: Pulmonary TB)								
Extrapulmo-nary TB	1.63 (1.23 - 2.17)	0.001	1.58 (1.15 - 2.18)	0.005	1.85 (1.22 - 2.79)	0.004	1.42 (0.90 - 2.25)	0.132
Both TB	3.21 (2.02 - 5.11)	<0.001	2.74 (1.67 - 4.48)	<0.001	1.53 (0.89 - 2.62)	0.122	3.92 (2.13 - 7.21)	< 0.001
Comorbidities (Reference: No for each comorbidity)								
Cancer	4.77 (2.54 - 8.96)	<0.001	3.21 (1.56 - 6.63)	0.002	3.33 (1.21 - 9.21)	0.020	2.88 (0.97 - 8.55)	0.057
HIV	2.67 (1.25 - 5.68)	0.011	2.24 (1.07 - 4.68)	0.033	0.57 (0.26 - 1.22)	0.145	3.81 (1.76 - 8.22)	0.001
Diabetes mel-litus	1.24 (0.91 - 1.67)	0.174	0.99 (0.67 - 1.46)	0.954	0.53 (0.29 - 0.96)	0.035	1.28 (0.81 - 2.02)	0.288
Asthma	0.51 (0.17 - 1.50)	0.221	0.57 (0.20 - 1.66)	0.306	1.35 (0.39 - 4.63)	0.635	0.45 (0.11 - 1.90)	0.276
Bronchitis	0.20 (0.05 - 0.91)	0.037	0.22 (0.05 - 0.98)	0.048	0.03 (0.00 - 0.22)	0.001	0.29 (0.06 - 1.37)	0.117
COPD	0.54 (0.35 - 0.84)	0.006	0.57 (0.36 - 0.90)	0.017	0.27 (0.09 - 0.78)	0.015	0.70 (0.43 - 1.15)	0.157
Osteoarthritis	0.09 (0.02 - 0.43)	0.003	0.10 (0.02 - 0.47)	0.004	0.06 (0.02 - 0.23)	< 0.001	0.11 (0.02 - 0.83)	0.032
Dorsopathies	1.01 (0.58 - 1.77)	0.973	0.72 (0.41 - 1.27)	0.257	0.55 (0.25 - 1.21)	0.137	0.80 (0.40 - 1.58)	0.517
Hyperuricemia & gout	1.55 (0.88 - 2.72)	0.128	1.47 (0.82 - 2.62)	0.195	1.59 (0.59 - 4.25)	0.357	1.38 (0.67 - 2.83)	0.384
Anemia	6.84 (4.55 - 10.28)	<0.001	5.69 (3.85 - 8.39)	<0.001	3.62 (2.18 - 6.01)	< 0.001	9.19 (5.80 - 14.54)	< 0.001
Heart failure	2.22 (1.29 - 3.83)	0.004	1.91 (0.89 - 4.11)	0.098	4.11 (1.55 - 10.88)	0.004	1.10 (0.44 - 2.80)	0.834

Variables	Unadjusted model		Adjusted model		Adjusted multi-state model			
			Mortality in 2 months		Mortality > 2 months			
	HR (95% CI)	p	HR (95% CI)	p	HR (95% CI)	p	HR (95% CI)	p
Hypertension	1.08 (0.68 - 1.70)	0.749	1.09 (0.68 - 1.74)	0.728	0.95 (0.29 - 3.09)	0.936	1.05 (0.63 - 1.76)	0.850
Dyslipidemia	0.50 (0.16 - 1.55)	0.227	0.52 (0.17 - 1.61)	0.258	0.45 (0.08 - 2.43)	0.355	0.58 (0.15 - 2.16)	0.412
Coronary artery disease	0.80 (0.46 - 1.39)	0.431	0.68 (0.35 - 1.29)	0.231	0.31 (0.10 - 0.98)	0.046	0.82 (0.39 - 1.74)	0.606

HR = Hazard ratio, p = Probability value, TB = Tuberculosis, HIV = Human immunodeficiency virus, COPD = Chronic obstructive pulmonary disease. Analyses were conducted using weighted data.

We observed that married individuals have a lower mortality risk, particularly in the long term. Studies have shown that family and spouse support can significantly improve treatment adherence (Deshmukh et al., 2018; Dilas et al., 2023). Such support can motivate patients, provide supervision during treatment, and facilitate health information seeking, leading to better treatment adherence (Dilas et al., 2023) and more favorable treatment outcomes. In addition, the fear of TB patients infecting their families motivates them to look for medical services actively. It can also drive patients to adhere to recommended health protocols, including taking prescribed medications consistently and following up with healthcare providers to ensure their condition is managed properly (Zimmerman et al., 2022).

Our study found that anemia, cancer, heart failure, and HIV infection are linked to an increased risk of mortality. However, only anemia has consistently shown a stable risk over time, while the risks for the other diseases varied over time. This highlights the importance of monitoring and managing individuals with TB and these conditions to ensure positive long-term health outcomes. While cancer, heart failure, and HIV infection have been associated with high mortality risks (Elhidsi et al., 2021; Min et al., 2019; Osei et al., 2020; Osman et al., 2021), anemia poses unique challenges in TB etiology and mortality. Anemia can make individuals more susceptible to TB infection, recurrence, and death, mainly due to iron deficiency (Chu et al., 2019). However, iron is crucial for *Mycobacterium tuberculosis* metabolism (Malik et al., 2020). Therefore, the treatment of anemia may have two side effects, and further research is needed to determine whether iron supplementation in individuals with TB and anemia is beneficial.

There is a crucial need for heightened monitoring of patients with comorbidities, as a time-varying association has been observed between mortality and specific conditions. During the intensive phase of treatment, cancer and heart failure have a significant impact on determining mortality, while HIV infection is associated with deaths over a more extended period. It is worth noting that death during the first two months of treatment is common and proportionally higher than at later stages (Birlie et al., 2015; Min et al., 2019). It's possible that this figure could be linked to either delayed TB treatment or drug intolerance (Birlie et al., 2015). Malignancy was associated with deaths during the intensive phase of treatment (Min et al., 2019), which aligns with our study findings. In cohorts with TB-HIV coinfection, increased age and decreasing CD4+ count are common predictors of death (Crabtree-Ramirez et al., 2022). This may explain the increased risks of mortality linked to HIV infection as time progresses.

Our findings indicated that asthma did not significantly impact mortality, whereas bronchitis and COPD showed protective effects. The reason for this could be attributed to the care-seeking process and the nature of the comorbidities. Patients who seek medical help and follow their treatment plan tend to have better outcomes (Gamtesa et al., 2020; Zimmerman et al., 2022). Patients with bronchitis or COPD may experience similar symptoms to TB, such as coughing, which drives them to seek care more frequently than those with asthma. This could also explain why patients with symptomatic comorbidities (e.g., osteoarthritis) tend to seek help more often than those with asymptomatic conditions (e.g., hypertension and dyslipidemia).

This is the first study in Indonesia that utilizes nationwide insurance claims data. Previous national studies in Indonesia (Iskandar et

al., 2023; Surendra et al., 2023) only focused on TB notification data, known as *Sistem Informasi Tuberkulosis*, which only provides information on TB patients. Our study is unique in that we can capture healthcare visits unrelated to TB, allowing us to explore the impact of comorbidities on healthcare outcomes. The longitudinal nature of the data enables us to explore the time-varying relationship between comorbidities and mortality. Therefore, this study can be an example of analyzing other diseases using a time-to-event administrative data approach. The relationship between comorbidities can indicate severity over time, allowing clinicians to monitor patients with specific comorbidities closely during critical periods.

We excluded many patients because we could not confirm if they were TB patients. We had limited clinical data; we only based our definition of comorbidities on diagnoses. Prescriptions and laboratory results could provide more insights not available in the current dataset. The mortality status was recorded during inpatient visits, and we could not assess the mortality outside the hospital setting. These limitations highlight the need to link healthcare services with other data, such as medical records or death registries. Although we modeled variables as time-varying covariates, we did not incorporate explicit latency periods between changes in these exposures and subsequent mortality risk, which may have led to temporal misclassification and biased effect estimates. Due to an imbalance in the number of cases across different years, we did not evaluate the impact of the COVID-19 pandemic on access to TB services and TB-related mortality. Several studies have indicated an increased mortality rate among patients with TB (Tavares et al., 2025), a decrease in TB case detection (Mashuri et al., 2024; Surendra et al., 2023; Vasquez et al., 2025), and a reduction in treatment success rates (Mashuri et al., 2024). Further research using BPJS sample data should examine the effects of COVID-19 on tuberculosis services and mortality.

CONCLUSION

Access to healthcare facilitated through UHC can help alleviate sociodemographic adverse impacts on healthcare outcomes. Anemia is a significant predictor of mortality, and its impact remains stable over time. Other comorbidities have varying risks over time, indicating specific times when heightened monitoring is necessary. These findings can assist clinicians in providing optimal care to TB patients. Our study overlooked some individuals who do not access TB care; therefore, future studies should include these individuals by linking the BPJS dataset with other administrative data, such as medical records, death registries, and other disease registries.

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