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Bayesian Survival Analysis of Adult Tuberculosis Patients at Lemlem Karl Hospital, Maichew, Southern Tigray, Ethiopia

Lemlem Tekle Berhe[1], Abrha Haftu Teklu[2], Lewtnesh Berihun Dangew[3*], Tsegay Gebrehiwot Gebru[4] and Netsanet Berhe Gidey[5]

[1]Department of Statistics, College of Natural and Computational Sciences, Raya University, Maichew, Ethiopia (lemlemtekle003@gmail.com; https://orcid.org/0009-0004-8581-0017).

[2]Department of Statistics, College of Natural and Computational Sciences, Mekelle University, Mekelle, Ethiopia (abrhahaftumu@gmail.com; https://orcid.org/0009-0006-1008-1184).

[3]Department of Statistics, College of Natural and Computational Sciences, Mekelle University, Mekelle, Ethiopia (*lewtnesh.berihun@mu.edu.et**;** https://orcid.org/0009-0004-6505-3717).

[4]Department of Health Data Science (HDS), University of Liverpool, England, United Kingdom (Tsegay.Gebru@liverpool.ac.uk).

[5]Faculty of Veterinary Sciences, College of Veterinary and Animal Sciences, Mekelle University, Mekelle, Ethiopia (netsanet.berhe@mu.edu.et**;** https://orcid.org/0000-0003-2873-1879).

ABSTRACT

Tuberculosis (TB) continues to be a significant issue on the agenda of the Southern Tigray population, and worldwide evidence regarding clinical and demographic factors affecting the survival of adult TB patients at the research site is lacking, which restricts the ability to provide evidence-based patient care and risk-stratified follow-up at the health-facility level. Thus, this research was performed in order to determine the factors that influence the survival of adult patients with tuberculosis who are treated at the Lemlem Karl Hospital Medical Center. It was a retrospective cohort study of 242 adult TB patients who registered between July 2020 and January 2024. Survival functions were compared using Kaplan-Meier curves and log-rank tests, and Bayesian survival models were fitted to determine the predictors of survival time. Out of the participants in the study, 178 (73.6) were censored, and the median survival was 26 months. The Bayesian log-normal accelerated failure time (AFT) model was the most suitable in light of the information. The variables that were significant predictors of the survival time were age, place of residence, baseline body weight, HIV status, BMI, anti-TB drug dose level, and cigarette smoking. Age (31-45, 46-60 and ≥61 years old), rural status, HIV positivity, high doses (III and IV), overweight and obesity, and cigarette smoking were factors that decreased the survival time of adult TB patients. Finally, the Bayesian log-normalized AFT model was found to be effective in explaining adult TB survival in this context and defining the major high-risk patient populations, and showed that clinical follow-up, combination of TB and HIV-based care, routine nutritional assessment, and specific tracking of older, rural, and clinically severe TB patients in Lemlem Karl Hospital were the priorities that needed to be reinforced.

Keywords: Tuberculosis, Bayesian, Survival Analysis, INLA, Accelerated Failure Time, Lemlem Karl Hospital, Tigray, Ethiopia.

1. INTRODUCTION

Tuberculosis (TB) is a serious infectious disease primarily affecting the lungs, though it can also involve other organs such as lymph nodes, brain, kidneys, bones, and intestines. It is caused by

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Mycobacterium tuberculosis and remains one of the leading causes of death from a single infectious agent worldwide, ranking above HIV/AIDS prior to the COVID-19 pandemic (Akan-nyaatemi et al., 2024; WHO, 2023). Although approximately one-quarter of the global population is infected with TB, most individuals do not develop active disease. TB is preventable and usually curable with timely diagnosis and appropriate treatment, which also reduces transmission and drug resistance. Globally, TB caused an estimated 1.3 million deaths in 2022, with about 10.6 million new cases reported, including a substantial burden among people living with HIV (WHO, 2023). Africa accounts for more than one-third of TB deaths, and Ethiopia remains among the high-burden countries, where TB continues to cause significant morbidity and mortality, particularly among vulnerable populations (UHC, 2023; Welekidan et al., 2020).

Although the incidence of TB is still high in Southern Tigray, Lemlem Karl Hospital regularly uses the descriptive reports of TB cases and treatment outcomes, and the survival-based analysis rarely to get patient-level risk factors of mortality and delayed treatment outcomes. Specifically, no local evidence is generated on how the demographic, clinical and nutritional factors, including age, residence, HIV status, BMI, baseline weight, disease severity and smoking, affect the survival time of adult TB patients, in Lemlem Karl Hospital. The current research on Ethiopia is largely undertaken within other areas and often employs the traditional Cox regression, and little by flexible Bayesian survival model to overcome the violation of proportional hazards and uncertainty in small or moderate hospital-based populations. Consequently, clinicians and program managers at the study site do not have evidence to determine high-risk groups of patients and to focus on follow-up and clinical monitoring.

Since, Bayesian survival analysis provides a flexible and powerful framework for analyzing time-to-event data, allowing the incorporation of prior information and yielding robust inference through parametric accelerated failure time (AFT) models (Ibrahim et al., 2001, 2011), the same Bayesian survival models are applied in this paper to identify the factors affecting the survival time of adult TB patients at Lemlem Karl Hospital, Maichew, Southern Tigray.

A study was conducted with the aim to determine the key prognostic factors, estimate survival time, compare parametric survival models, and explore Bayesian AFT models using the Integrated Nested Laplace Approximation (INLA) approach. The objective of the study was to identify and model the factors affecting the survival time of adult tuberculosis patients treated at Lemlem Karl Hospital using Bayesian survival analysis. Specifically, the study aims to estimate

the survival time of adult tuberculosis patients and to identify the effects of demographic factors, such as age and place of residence, on their survival time. It also seeks to assess the influence of clinical and comorbidity-related factors, including HIV status and disease severity, on patient survival. In addition, the study will evaluate the impact of nutritional indicators, such as body mass index and baseline body weight, on the survival time of adult TB patients, and examine the association between behavioral factors, such as smoking, and survival outcomes. Furthermore, the study aims to compare different parametric survival models for modeling the survival time of adult TB patients and to apply Bayesian accelerated failure time (AFT) models for survival analysis. Finally, it will explore the use of the Integrated Nested Laplace Approximation (INLA) approach for Bayesian survival modeling in a hospital-based tuberculosis cohort.

2. METHODOLOGY

2.1. Study Area and Study Design

The data was taken from Lemlem Karl Hospital Medical Center (LKHMC), Maichew, southern Tigray. Maichew is a small town about 665 Km north of Addis Ababa and 130 Km from Mekelle, the capital of Tigray State. A retrospective study has been applied to obtain data on HF patients that recorded in LKHMC. Only adult TB patients who had been registered at LKHMC starting from July 2020 up to January 2024 are considered in the study. The data has been carefully reviewed using registration log book and patient's registration card. In case of inadequate information, the data was checked from the file and excluded from the analysis if proven inadequate. Thus, the data has been collected from the patient follow up records.

2.1.1. Inclusion and Exclusion Criteria

2.1.1.1. Inclusion criteria

All TB patients with complete medical records of (gender, age, residence, HIV status, dose of drugs, BMI, cigarette smoking, baseline weight, previous TB status, and type of TB) who registered in the hospitals from July 2020 to January 2024 and whose age greater or equal to18 years old were included.

2.1.1.2. Exclusion Criteria

TB patients whose medical records with missing values on the variables of interest, gender, age, residence, HIV status, cigarette smoking, body weight, previous TB status dose of drugs, and type of TB was excluded. TB patients with the age less than 18 years old were excluded.

2.2. Data Collection Methods

Ethical permission has been obtained from LKHMC, and the secondary data were taken based on the existing data in the hospital by the trained enumerator and the principal investigator using check list (data extraction form). The quality of data was taken care of in terms of standardization of data definitions, completeness checks, range checks, logical consistency checks, duplicate checking and random checking of the sampled records with the original hospital registration documents. All the data cleaning and validation processes were recorded to make the analysis transparent and reproducible.

2.2.1. Starting Time

The start time of the interval (in months). Time origin or the beginning of the study, the entry of the survival data would be considered from the day that the adult TB patients starts diagnosis; when the patient first received the treatment.

2.2.2. Ending Time

The time (in months) at which the event was occurred, when the adult TB patients was died or was lost to follow-up by January 2024 (at the end of study). This means that the type of the survival data is rightly censored.

2.3. Variables in the Study

The dependent variable, the survival time of Adult TB patients (in months), which is defined as the difference between the time of diagnosis and time to one of the events “death”, “lost to follow-up”, “dropped out”, “stopped”, “transferred out to other health centers or hospitals” occurred. Death was considered an event of interest. The status variable was 0 for censored and 1 for death. The factors considered for the purpose of Bayesian survival analysis of adult TB patients include, Age, BMI, Sex, Cigarette Smoking, Residence, HIV Status, Type of TB, Dose of drugs, Previous TB, Baseline Weight.

2.4. Method of Data Analysis

The secondary data were extracted using a structured checklist by the trained enumerators and the principal investigator and then subjected to routine data cleaning, completeness, consistency and verification processes. Mean imputation were applied to handle missing data.

2.4.1. Descriptive Statistics

The description of survival data utilizes non-parametric methods to compare the survival functions of two or more groups and kaplan-meier plots would be employed for this purpose

(Kaplan and Meier, 1958). The frequency distribution table was used to summarize the data obtained from registration book of patients based on the study variables in LKHMC Maichew, Southern Tigray.

2.4.2. Survival Data Analysis

Survival analysis considers a key analytic problem of censoring that occurs when some information about individual survival time is known, but not the exact survival time (Aalen et al., 2008). Survival analysis is well suited for adult TB data-set which are very common in medical research since studies in medical areas have a special feature that follow-up studies could start at a certain observation time and could end before all experimental units experience an event. Death was considered the event of interest.

2.4.2.1. Right Censoring

Occurs when a subject leaves the study before an event occurs, or the study ends before the event has occurred (Lunn et al., 2012). Survival time is said to be right censored when it is recorded from its beginning to a defined time before its end time. This type of censoring is commonly recognized in survival analysis (Lunn et al., 2012) and is considered in the study. Patients who lost to follow-up, transferred out, dropped out, or stopped treatment before experiencing death were treated as right-censored observations, because their exact survival time beyond the last recorded follow-up was unknown and no information on subsequent vital status was available.

2.4.3. Estimation of Survival Function

The Kaplan-Meier estimator, non-parametric estimator used to estimate the survival function with censoring, which is not based on the actual observed event and censoring times, but rather on the order in which events and censored observations occur (Kaplan and Meier, 1958). Therefore, the Kaplan Meier estimate of the survival function at time t, (S (t)) is given by:

$$\hat{S}(t) = \prod_{j;rj \le t}(1 - \frac{dj}{rj}) \qquad (1)$$

Where, rj represents the set of k distinct death time in the observed in the sample,
rj is the of subjects alive (at risk) just before time t_j (the j^{th} ordered survival time), and
dj denotes number who died at time.

2.4.4. Comparison of Survival Function

The Kaplan-Meier plots are used to see whether there is difference in survival times or not between groups of covariates under investigation. But, the plot cannot be used to decide whether

the survival time of TB patients in each covariate is different or not and log-rank test was used for this purpose (Mantel and Haenszel, 1959). The test statistic for log rank test is given by:

$$X^2 \log \text{rank} = \frac{[\sum(doj - roj\frac{dj}{rj})]^2}{\sum \frac{rojr1jdj(rj-dj)}{r^2 j(1-rj)}} \sim X^2 \qquad (2)$$

Where, d_{0j} is the number of failure in j^{th} time of 1^{st} group;
d_{1j} the number of failures in j^{th} time of 2^{nd} group;
d_j is the number of failure in j^{th} time ($d_{0j} + d_{1j}$);
r_{0j} is the number at risk at j^{th} time of 1^{st} group;
r_{1j} is the number at risk at j^{th} time of 2^{nd} group, and
r_j the number at risk at j^{th} time ($r_{0j} + r_{1j}$).

The hypotheses to be tested are:

$H0$: There is no difference between the survival curves.

$H1$: There is difference between the survival curves.

2.5. Bayesian Survival Analysis

Bayesian approach is preferred over the frequentist approach in survival analysis is that the power of information obtained from the approach is much better as it is the combination of likelihood data and prior information about the distribution of the parameter. With the use of the Gibbs sampler and other MCMC techniques, fitting complex survival models is straightforward, and the availability of software like BUGS eases the implementation greatly (Ibrahim et al., 2001). MCMC methods, has some limitation like the burden of time in approximating the posterior and convergence problem (Brooks and Gelman, 1998; Berger, 2013). As of 2009, the other news was welcomed with very flexible and fast approximation techniques called Integrated Nested Laplace Approximation. Bayesian approach with INLA method is focused on providing a good approximation to the posterior marginal distributions of the parameters in the model (Rue et al., 2009).

The reason to choose Bayesian statistics is to produce more accurate parameter estimates. In addition, Bayesian statistics one can incorporate uncertainty about a parameter and update this knowledge through the prior distribution (Depaoli, 2014). Bayesian approach considers the parameters of the model as random variables and requires that prior distributions be specified for them and data are considered as fixed.

2.5.1. Components of Bayesian inference

2.5.1.1. Prior Distribution

-$\pi(\theta)$, is a probability distribution that represents uncertainty about an unknown parameter θ before observing data. It is called the prior distribution and reflects prior knowledge about the parameter of interest. A conjugate prior is chosen so that it yields a posterior distribution in the same family. When no prior information is available, a uniform distribution is commonly used as a non-informative prior (Ibrahim et al., 2001).

2.5.1.2. Likelihood

Ł(θ|Data), it is a likelihood functions, which is a function that gives the probability of observing of the sample data given the current parameters. For set of unknown parameters in the presence of right censoring it can be written as (Ganjali and Baghfalaki, 2012):

$$L(\theta|Data) = [f(ti\,|Xi\,;\,\theta)^{\sigma i} * S(ti\,|Xi\,;\,\theta)^{1-\sigma i}] \quad (3)$$

Where, σ_i is censoring indicator (0 = censored and 1 = death);
$f(t_i\,|X_i\,;\,\theta)$ is probability density; and
$S(t_i\,|X_i\,;\,\theta)$ is the survival distribution.

2.5.1.3. Posterior Distribution

Posterior Distribution is a combination of prior distribution and likelihood using the Bayes rule, likelihood which includes information about model parameters based on the observed data, and a prior, which includes prior information (before observing the data) about model parameters. It is obtained by multiplying the prior distribution over all parameters, θ, by the full likelihood function L(θ|X) (Christensen et al., 2011). The Posterior Distribution given by:

$$\text{Posterior} = \frac{Likelihhod*prior}{\int Likelihood*priord\theta} \quad (4)$$

Assuming that θ is a random variable and has a prior distribution denoted by $\pi(\theta)$, then posterior distribution,$\pi(\theta|X), of\ \theta$ is given by:

$$-\pi(\theta|X) = \frac{L(X|\theta)\pi(\theta)}{\int L(X|\theta)\pi(\theta)d\theta}. \quad (5)$$

Parametric models play an important role in Bayesian survival analysis, since many Bayesian analyses in practice are carried out using parametric models (Exponential Model, Weibull Model, Log-Normal Model, and Log-Logistic Model). Parametric modeling offers straightforward modeling and analysis techniques (Ibrahim et al., 2001).

2.5.2. Estimation of Parameter in Bayesian Survival Models

2.5.2.1. Integrated Nested Laplace Approximation (INLA) Method

The Integrated Nested Laplace Approximation Method was used to estimate the parameters in the Bayesian survival model. According to Akerkar et al. (2010), INLA computes posterior marginals for each component in the model and it is from these that the posterior expectations and standard deviations can be found. The survival models can be expressed as a latent Gaussian model on which the integrated nested Lap-lace approximations can be applied (Akerkar et al., 2010). The main aim is to approximate the posterior marginals of the latent field, π (Xi |Y) and the posterior marginals of the hyper parameters π (θ|Y) and π (θj |Y). The posterior marginals are given by:

$$\pi(Xi\,|Y) \;=\; \int \pi\,(Xi|\theta)\;\pi(\theta|\,Y)d\theta \qquad (6)$$

$$\Pi\,(\theta j\,|Y) = \int \pi(\theta/Y)\mathrm{d}\theta - j \qquad (7)$$

Where, π (Xi |Y), π(θ|Y) and π (θj |Y) are the posterior marginals to be approximated by the latent gaussian models.

INLA is a great improvement in speed compared to the other MCMCs and also a higher level of accuracy (Akerkar et al., 2010). In addition, INLA provides both extremely fast and very accurate approximations to the posterior marginal through a clever use of lap-lace approximations and advanced numerical methods and it can be adapted to fit survival models.

2.5.3. Bayesian Model Selection Criterion

Because a Bayesian modeling framework was used, p-values and classical stepwise variable selection procedures (forward or backward) were not applied; instead, variables were selected based on subject-matter relevance and Bayesian model comparison, and statistical inference was based on posterior credible intervals.

For Bayesian models, this study preferred the Deviance Information Criteria was used for Bayesian survival model comparison. The preferable model is the one with the lowest value of the DIC (Spiegelhalter et al., 2004).

2.5.4. Bayesian Model Diagnostics

The most common ways of checking goodness of fit are: Bayesian Cox-Snell residual plot and Predictive Distribution. Model checking and adequacy play an important role in models for survival data. In Bayesian analysis, Chaloner (1991) defined the Bayesian version of the

residuals. The idea on how to classify the sample data and techniques undergone for the application of criticism for predictive distribution (Piironen and Vehtari, 2017).

3. RESULTS

3.1. Description of Study Participants and Descriptive Survival Analysis

The data for this study has been taken from 242 adult patients receive treatments for adult TB, at least one time, at LKH Medical Center, Maichew, Southern Tigray from July 2020 up to January 2024. The minimum and maximum event time observed from adult TB patients follow up where 7 and 43 months respectively. Among adult TB patients, about 26.4% died and remained were censored. Fifty percent of adult TB patients who receive treatments survived 26 months or above. Almost half, 50.40%, of the adult TB patients, were female and the remaining were male during the follow-up study. However, the survival time of female patients seems lower.

By observing the HIV status of adult TB patients, it was found that 33(13.64%) were HIV-negative, while 209(86.36%) were HIV positive. Additionally, 51.65% of adult TB patients had a body mass index categorized as underweight, 41.32% had a normal body mass index, 0.83% were classified as overweight, and 6.2% were considered obese. The distribution of adult TB patients across drug dose levels showed 57.44% (139) were on dose level II, 2.51% (69) on dose level III, and 14.05% (34) on dose level IV. Out of the TB patients, 59.5% (144) were diagnosed with pulmonary, while 40.5 % (98) had extra-pulmonary TB.

3.2. The Kaplan Meier Estimate for some Covariate

Figure 1 presents the Kaplan-Meier survival estimate of the survival curves of adult TB patients during the study period. The estimated survivor function with 95% confidence interval, provides a descriptive measure of the overall pattern on survival time. The survivorship probability remained relatively constant during the first 10 months of follow-up, after which it gradually declined up to 40 months. The survivor function didn’t reach zero, as the longest observed survival time corresponded to a censored observation.

The 95% Confidence Interval (CI) in this graph, the shaded band around the line represents the range in which we are 95% confident that the true survival probability lies. Because it is a survival curve, the confidence interval gets wider (the band gets thicker) as time goes on because there is less data (fewer patients remaining) at the later time points.

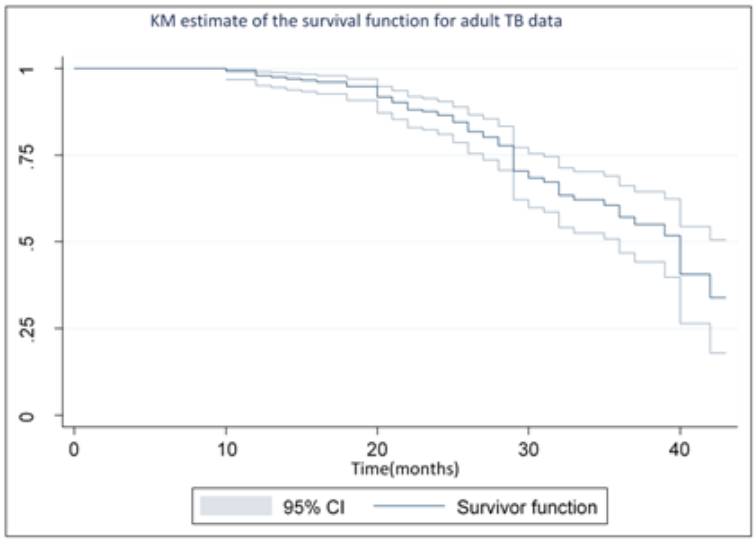


Figure 1. Kaplan-Meier estimates of the survival curves of adult TB data set. Overall survivor function for adult TB patients in the study (Y-axis represents the estimated probability of surviving up to a given time point).

Figure 2 shows the Kaplan-Meier survival curves of the adult TB patients in the various age groups in the follow-up period. The curves indicate the variation in the probability of survival with time with respect to the age category.

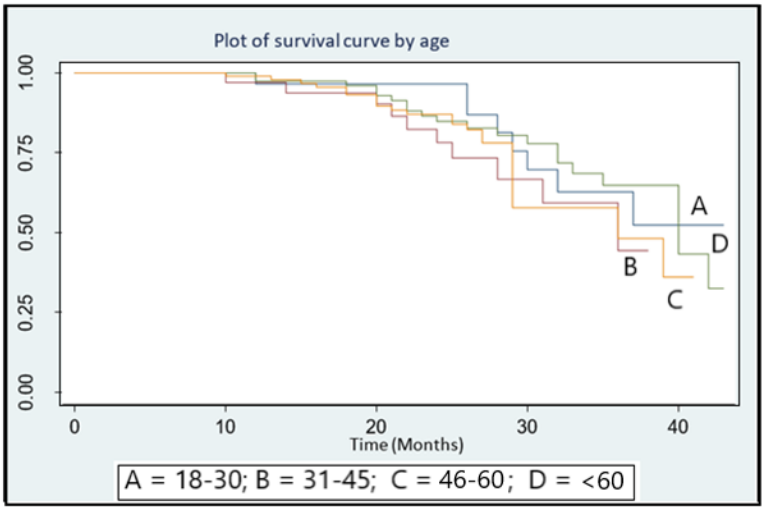


Figure 2. Kaplan-Meier estimates of the survival curves of adult TB patients by age groups.

Comprehensively, the probability of survival is reduced with time, meaning that their occurrences of deaths due to treatment or follow-up. The fact that there is some difference in the curves (Fig 2) imply that age is a factor that determines the survival of TB patients. The older age groups are more prone to survival over the long run since the curves are higher on the graph. Conversely, the survival probability of older age groups is more sloping down. This points to the

fact that elderly patients are at a strong risk of death than young patients. As such, age seems to be a significant determinant that influences the survival of the adult TB patients.

3.3. Checking the Assumption of Cox-PH

As it can be seen in the table 1, the p-values for HIV status and dose level are less than common (5%) level of significance using correlation test (rho) and these shows as the assumption of Cox-PH model was not valid for adult TB data set.

Table 1. Shows test of assumption in Cox-PH model.

Covariates	***rho***	***chi2***	***df***	***p-value***
Age	0.06444	0.29	3	0.5887
Sex	-0.18490	2.40	1	0.1211
Residence	-0.03436	0.09	1	0.7695
Previous TB	-0.00530	0.00	1	0.9654
TB type	0.03421	0.07	1	0.7889
HIV status	-0.31147	7.27	1	0.0070
Dose level	-0.14040	1.49	2	0.0228
Cigarette smoking	0.05175	0.19	1	0.6632
BMI	-0.13963	1.40	3	0.2360
Base line weight	-0.2367	0.34	1	0.4154
global test		11.14	15	0.00664

3.5. Bayesian Survival Data Analysis

As shown in table 1, the assumption of the Cox-PH model was not valid for the adult TB data. In the present case, a parametric AFT model was used for the adult TB data. We assume that the scale parameter has a gamma prior with shape parameter 1 and inverse scale parameter 0.001, this prior was used for Weibull, Log-normal and Log-logistic distribution for INLA and MCMC method of estimation (Ouabi et al., 2022; Ibrahim et al., 2001).

Table 2. Comparisons of Bayesian A FT model using MCMC and INLA methods.

Distribution	***MCMC***		***INLA***	
	PD	***DIC***	***DIC***	***WAIC***
Exponential	14.664	1397.04	1300.62	1422.98
Weibull	15.460	1311.06	1289.20	1283.33
Log normal	**15.786**	**1221.63**	**1197.64**	**1197.36**
Log-logistic	16.321	1286.64	1226.88	1226.27

Table 2 shows the analysis of the adult TB data set for model comparison using MCMC and INLA methods. To compare the efficiency of these different models DIC and WAIC were used and the one with the smallest value seemed best fit. Accordingly, the Bayesian lognormal

AFT model using INLA (DIC = 1197.64; WAIC = 1197.36) and Bayesian log-normal AFT model using MCMC Method (DIC = 1221.63) were found to be the best for survival time of adult TB patients' data from the given alternative.

3.6. Bayesian Log-Normal AFT Model using INLA Method

The final results for the Bayesian log-normal AFT model using INLA method shown in table 3. The result shows that the survival time of adult TB patients statistically significantly affected by age, residence, HIV status, dose level, body mass index, base line weight and cigarette smoking of adult TB patients.

3.7. Interpretation of Bayesian log-normal AFT model using INLA Method

Table 3 presents the final Bayesian log-normal accelerated failure time (AFT) model, with effects interpreted using acceleration factors and their corresponding 95% credible intervals (CrIs). An acceleration factor less than one indicates a reduction in expected survival time relative to the reference category.

Table 3. Indicating the results for Bayesian log-normal AFT model using INLA method.

Covariate	***Category***	***PM***	***Sd***	***Median***	***CrI***	***Mode***	***Kid***
	Intercept	3.84	0.213	3.856	[3.541,4.309]*	3.817	**0**
Age	18-30	Ref					
	31-45	-0.15	0.113	-0.346	[-0.288,-0.046]*	-0.245	0
	46-60	-0.33	0.110	-0.245	[-0.457,- 0.025]*	-0.213	0
	>60	-0.41	0.110	-0.486	[-0.672,-0.027]*	-0.389	0
Residence	Urban	Ref					
	Rural	-0.30	0.076	-0.200	[-0.352,-0.053]*	-0.299	0
HIV status	HIV-	Ref					
	HIV+	-0.38	0.075	-0.277	[-0.437,-0.144]*	-0.387	0
Dose level	II	Ref					
	III	-0.42	0.176	-0.318	[-0.681,- 0.080]*	-0.410	0
	IV	-0.50	0.173	-0.421	[-0.857,-0.180]*	-0.492	0
BMI	Underweight	Ref					
	Normal	-0.14	0.102	-0.144	[-0.291, 0.052]	-0.155	0
	Overweight	-0.15	0.113	-0.143	[-0282,- 0.043]	-0.157	0
	Obese	-0.25	0.115	-0.246	[-0.386,- 0.024]*	-0.235	0
Cigarette smoking	No	Ref					
	Yes	-0.15	0.073	-0.145	[-0.157,-0.001]*	-0.147	0
Baseline weight	<=50	Ref					
	>50	-0.14	0.062		[-0.100,-0.012]*	-0.132	0
Tau parameter	for log-normal	4.12	0.386	3.27	[2.38, 4.33]*	3.27	0

Note: * = Statistically significant variables that affect the survival time of adult TB patients.

After adjusting for other covariates, age showed a significant association with survival among adult TB patients. Compared with patients aged 18–30 years, those aged 31–45, 46–60, and above 60 years had acceleration factors of 0.8607 (95% CrI: 0.749–0.9550), 0.7189 (95% CrI: 0.6332–0.9753), and 0.6637 (95% CrI: 0.5107–0.9734), respectively. This corresponds to reduction in expected survival time of 13.93%, 28.11%, and 33.63%. Since the credible intervals do not include 1, age had a statistically significant effect on survival, with older age groups experiencing progressively shorter survival times.

Residence was also a significant predictor. Adult TB patients residing in rural areas had an acceleration factor of 0.7408 (95% CrI: 0.7033–0.9484), indicating a 25.92% shorter expected survival time compared with urban residents. Similarly, HIV-positive patients experienced substantially reduced survival, with an acceleration factor of 0.6839 (95% CrI: 0.6459–0.8658), reflecting a 31.61% decrease relative to HIV-negative patients.

Body mass index (BMI) significantly influenced survival outcomes. Overweight and obese patients had acceleration factors of 0.8607 (95% CrI: 0.7543–0.9579) and 0.7790 (95% CrI: 0.6798–0.9763), respectively, indicating lower survival compared with underweight patients, while normal BMI was not significant. Disease severity further reduced survival, as stage III and IV patients had significantly lower survival times than stage II patients. Baseline body weight and smoking status were also significant. Patients with baseline weight above 50 kg and those who smoked had reduced expected survival times compared with their reference groups.

Finally, the Kullback–Leibler divergence values for all significant parameters were zero, indicating that posterior distributions were well approximated by normal distributions. Therefore, the simplified Laplace approximation was appropriate and computationally efficient for Bayesian inference.

3.8. Bayesian Model Diagnostics

3.8.1. Bayesian Cox Snell Residual Plots

The Cox–Snell residual plots were used to assess the goodness-of-fit of the four Bayesian AFT models. The Weibull AFT model showed a reasonable fit, although slight deviations from the 45° reference line were observed, particularly at higher residual values (Fig 3).

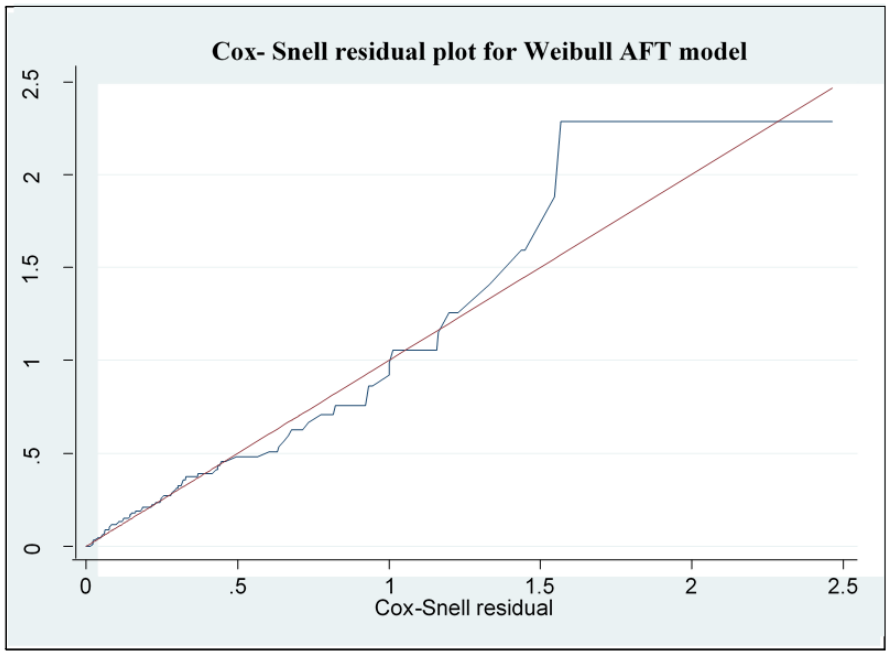


Figure 3. Bayesian Cox- Snell residual plot for Weibull AFT model.

The exponential AFT model exhibited more pronounced departures from the straight line, indicating a poorer fit to the data (Fig 4).

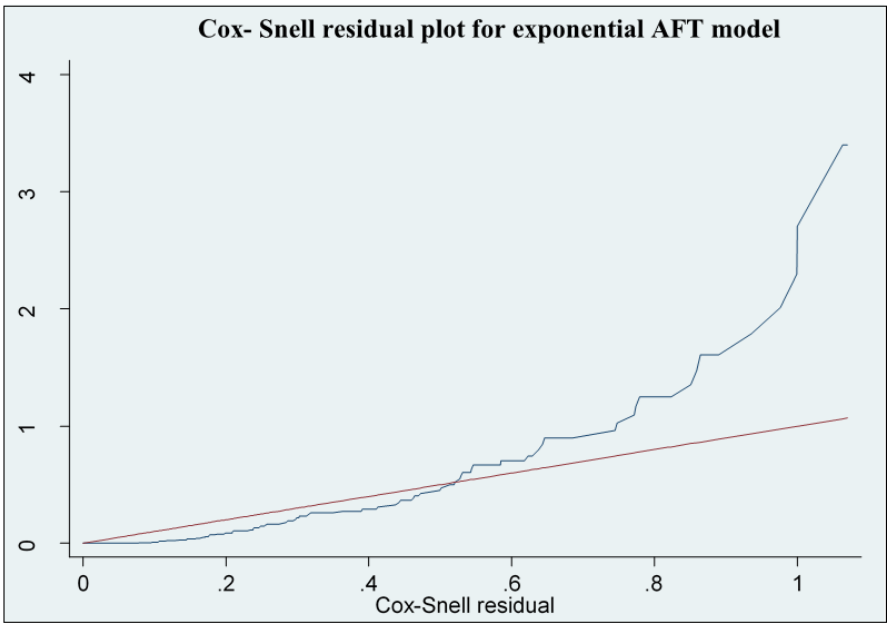


Figure 4. Bayesian Cox- Snell residual plot for exponential AFT model.

The log-logistic AFT model demonstrated an improved fit compared to the Weibull and exponential models, though some deviations were still evident, especially in the tails (Fig 5). Overall, the Bayesian log-normal AFT model provided the best fit to the adult TB dataset, as its

Cox–Snell residuals closely followed a straight line with slope one and lay nearest to the line through the origin, suggesting that it most adequately captured the underlying survival distribution among the four models (Fig 6).

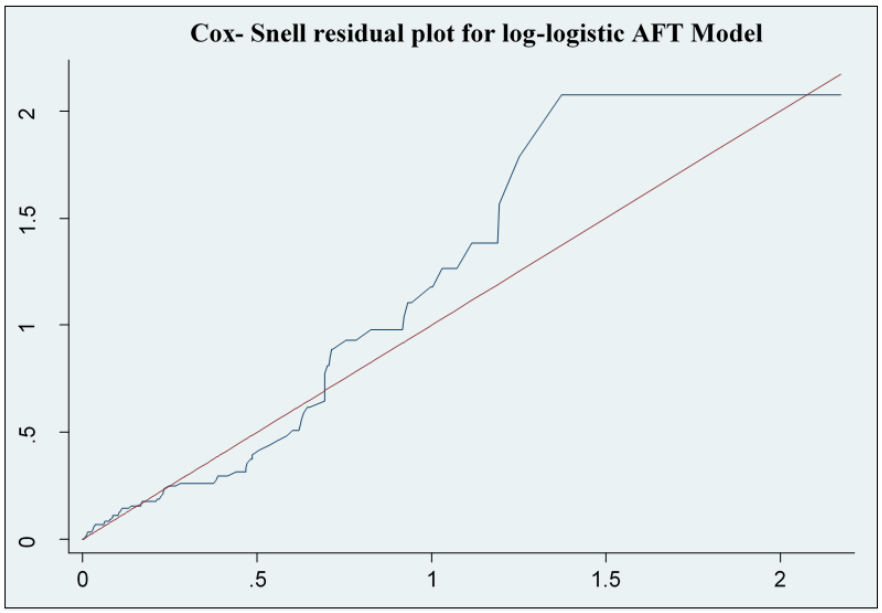


Figure 5. Bayesian Cox- Snell residual plot for log-logistic AFT Model.

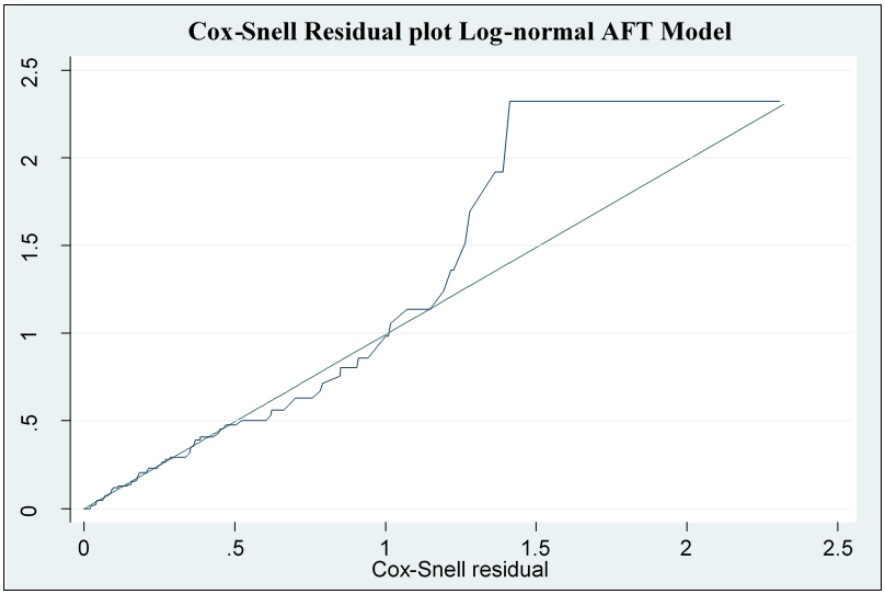


Figure 6. Bayesian Cox-Snell Residual plot Log-normal AFT Model.

4. DISCUSSION

The primary objective of this study was to identify factors influencing the survival time of adult TB patients using data from LKH, Maichew, and Southern Tigray. Tuberculosis remains a major

global public health problem, with prevalence among adults in developing countries ranging from 8% to 15% and increasing with age (Adebayo et al., 2017). A total of 242 adult TB patients were included, with observed follow-up times ranging from 7 to 43 months and a median survival time of 26 months.

The Bayesian log-normal AFT model fitted using the INLA approach revealed that age, residence, HIV status, dose level, baseline weight, cigarette smoking, and BMI significantly affected survival time. Older age groups (31–45, 46–60, and >60 years) exhibited significantly shorter survival times compared with patients aged 18–30 years, consistent with previous studies indicating increased TB-related mortality with advancing age (Addis et al., 2022). HIV-positive patients had substantially lower survival probabilities than HIV-negative patients, corroborating findings from earlier studies (Masini et al., 2016; Geleso, 2020b), although contradictory evidence exists in some settings (Alobu et al., 2014; Aljohaney, 2018).

Disease severity, reflected by higher anti-TB drug dose levels (III and IV), was associated with reduced survival, aligning partially with prior evidence, though some studies reported non-significant effects due to limited resistant cases (Xie et al., 2020). BMI and residence were also important predictors, with overweight, obesity, and rural residence associated with shorter survival, consistent with earlier findings (Adane et al., 2020; Kassa et al., 2020; Geleso, 2020a; Addis et al., 2022). Baseline body weight further highlighted the role of nutritional status in TB outcomes (Birlie et al., 2015; Asantha et al., 2008).

Model diagnostics confirmed that the Bayesian log-normal AFT model provided the best fit, with zero Kullback–Leibler divergence values indicating high accuracy of the INLA approximation. Despite these strengths, the study was limited by reliance on secondary data and the absence of key prognostic variables such as diabetes and alcohol use.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

In conclusion, this study demonstrated that the Bayesian log-normal accelerated failure time (AFT) model fitted using the INLA approach provided the best performance for analyzing adult TB survival data. The median survival time of adult TB patients was 26 months. Survival time was significantly influenced by age, residence, HIV status, BMI, dose level, baseline weight, and

cigarette smoking. Older age, rural residence, HIV positivity, overweight or obesity, and smoking were associated with reduced survival among adult TB patients.

5.2. Recommendations

1. Clinical follow-up intensification as part of the TB treatment should be focused on older patients aged greater than 31 years, especially on patients aged 46 years and older, and closer monitoring of the patients during the intensive stage of the treatment.
2. TB-HIV integrated services should be routine and enhanced in Lemlem Karl Hospital and other related facilities, with early HIV testing, timely use of antiretroviral therapy, and follow-up of co-infected patients to ensure proper follow-ups since HIV was a high rank factor of poor survival.
3. Nutrition evaluation and intervention must be planned as part of TB treatment with the routine monitoring of baseline body weight and BMI at the time of treatment and during follow-up and the administration of specific nutrition supplements to patients with abnormal nutritional status.
4. Access and follow-up, including community-based treatment support, enhanced health extension worker involvement, and follow-up defaulter tracing systems, should be provided to rural TB patients, to resolve the observed disadvantage in survival of rural residents.
5. Patients who have advanced disease (greater levels III and IV dose) ought to undergo early clinical risk stratification comprising of closer clinical follow-up, prompt referral on the development of complications, and prompt identification of treatment failure or resistance to drugs.
6. Smoking cessation counselling must be integrated into regular TB treatment care and TB clinics should offer brief behavioral interventions and referral to the available cessation support services to smoking patients.

Lastly, to enhance future research on TB survival and patient management, regular hospital registration systems need to be enhanced to encompass the most critical prognostic variables, including diabetes status and alcohol consumption, and prospective studies ought to be performed in the future to verify the current results and evaluate the effect of the additional risk factor on TB survival in southern Tigray.

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7. CONFLICT OF INTERESTS

There is no conflict of interests.

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