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Research Article

Under-Five Pneumonia Patients in Menz Geramidr Mehalmeda Hospital North Shewa, Ethiopia:Bayesian Parametric Survival Model

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ABSTRACT

Background: Pneumonia is that the most wanted largest infectious reason for death in children worldwide. It's most prevalent in South Asia and geographic region. In Ethiopia, pneumonia could be a leading single disease killing under-five children. Parametric survival analysis is defined as a group of longitudinal analysis methods for interrogating data having time as an outcome variable and Bayesian analysis is employed to boost the precision of the results by introducing external information in terms of the prior distribution. The aim of this study was to analyze the survival rate of under-five pneumonia patients in Menz Gera Mehalmeda Hospital using Bayesian survival analysis.

Methodology: Retrospective study was conducted in Menz Gera Mehalmeda Hospital from September1,2002 up to August 30,2020. Children whose age between greater than 29 days and less than five year were included within the study and Patients with insufficient information were excluded from the study. The parametric classical AFT models and Bayesian AFT models were used for the analysis.

Result: The results implied that patients whose residence were urban, male patients, age groups of patient at the age (12-23) months, (24-35) months, (36-47) months and (48-59) months, patients without comorbidity, patients without severe acute malnutrition (SAM), was prolonged timing death of under-five pneumonia patients, while female patients, age of patients at the age of(1-11) months, patients with comorbidity, patients whose residence was rural and patients with severe acute malnutrition (SAM) were statistically significantly shorten timing of death.

Conclusion: Finally, the findings of this study implied that the sex of children, residence of children, age of children, Co-morbidity, Severe Acute Malnutrition(SAM) and weight were major factors related to survival time of under-five pneumonia patients in Menz Gera Mehalmeda Hospital.

Keywords: Pneumonia, Under-five, Survival analysis, Bayesian analysis, MCMC simulation.

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INTRODUCTION

Acute pneumonia is defined as an acute infection affecting the lungs (WHO 2019). this can be a number one reason for morbidity and mortality, particularly in children younger than 5 years with 704,000 deaths and 60.6 million Disability-Adjusted Life Years (DALYs) supported data from 2015 (GBD 2015). The annual incidence of clinical pneumonia in younger children in low-income countries was estimated at 231 episodes per 1000 children in 2015 (McAllister DA *et al.,* 2019). In developing countries, the diagnosis of pneumonia mostly relies on clinical examination because of lacking imaging and laboratory capacities. In 2005, World Health Organization (WHO) proposed that acute respiratory infections be divided into three categories including non-pneumonia tract infection, pneumonia, and severe pneumonia in keeping with clinical criteria (WHO 2019). In countries with high incidence of lung infection, 20% of pneumonia are severe and need hospitalizing (Scott *et al.,* 2012, Nair *et al.,* 2013). About 15% of all deaths in children <5 years old are thanks to pneumonia within the WHO Western Pacific region, with over 75% cases in Cambodia, Laos, Vietnam, China, and Philippines (Nguyen *et al.,* 2017). Antibiotics are effective if administered on time in bacterial pneumonia. However, only 70% of pneumonia cases receive an appropriate antibiotic within the developing world (WHO 2011). There's not one or specific and easy mean to stop this disease. Therefore, the identification of risk factors for pneumonia and notably for severe disease is important.

According to 2012 central statistical agency report there's high burden of pneumonia in Ethiopia that's 88 in 1,000 children under age 5 die before their fifth birthday (CSA 2012).

In this area there was tried works to use statistical models to spot the determining factors of pneumonia and several other studies were about the prevalence of the pneumonia. Because of this during this paper the researcher target the survival time of patients hospitalized and also includes the hospital level variables during this study.

Length of hospital Stay (LOS) is one in every of hospital level variable which is measured from patient's admission in hospital up to discharge of patients from hospital.

Survival analysis could be a statistical procedure for data analysis where the result variable of interest is that the time to the occurrence of an incident and there are many standard parametric models like Weibull, Lognormal and log logistic are accelerated failure time models (Klein *et al.,* 2003).

Modeling survival data using Cox proportional hazards regression is popular for its robust to the unknown baseline hazard (Cox DR., 1992). Alternatively, being well-known for parametric survival analysis, Accelerated Failure Time (AFT) model tends to present more precise estimates of interest parameters if the distribution of survival time is chosen correctly, additionally, the parameter estimates from AFT are robust to omitted covariates (Keiding N *et al.,* 1997).

METHODOLOGY

This study was a retrospective study that reviews or visits all under-five aged children cards hospitalized with Pneumonia in Menz Gera Mehalmeda Hospital. The population of this study was all under-five aged children hospitalized with pneumonia who had been registered at Mehalmeda Hospital from September 1, 2012 up to August 30, 2020. All the info will carefully reviewed from the registration log book and patients' registration card; any inadequate information was countered and checked from the file and excluded from analysis if proven to be inadequate. The cards were prepared by Federal Ministry of Health to be uniformly employed by clinicians to early identify and document clinical and laboratory variables. A complete of 811 under-five aged children hospitalized with pneumonia were recorded with full information in given study period of your time, that the researcher select the sample size from those population.

Data collection procedure

The data for this study is secondary data that will recorded on pediatric registration chart and cards via nurses, laboratory technicians, medical doctors and clinicians. The hospital's registry is used to extract data of under-five pneumonia and patients' initial date of admission up to discharge of patients. During the study period, the pediatric record logbook and the patient's identification cards are use in order to select the variables in the study by trained clinicians. The complete data collection forms are examine for completeness and consistency during data management, storage and analysis.

Response variable

The response variable is time to event (time to death) of under-five aged children hospitalized with pneumonia and it is defined as status variable (event occurred or censored).

Independent variables

The predictor variables (factors) are variables that are assumed to influence the survival time of under-five aged children hospitalized with pneumonia in MehalmedaHospital. These variables are selected based on some previous study conducted, at Tanzania Lake Zone's public hospitals (Kristina L *et al.,* 2017). The variables that are expected to be the factors/determinants of mortality of under-five aged children hospitalized with pneumonia are as follows.

The variables included in this paper are:

Table 1

Continuous variables in the study

WeightWeight of the children

Bed Occupancy Rate

(BOR) The percentage of official beds occupied by hospital

Inpatients for a given period of time

$$BOR = \frac{(\text{Total length of hospital stay in a given month})}{30 \times \text{Number of beds in that month}}$$

Patient: Nurse RatioRatio of patient to nurse counted in a month

(PNR) $$BOR = \frac{(\text{Total length of hospital stay in a given month})}{30 \times \text{Number of beds in that month}}$$

Patient: Physician Ratio of patient to physician counted in a given month;

(PPhR) $$PPhR = \frac{\text{Number of patients admitted in a given month}}{\text{Number of physician on service in a given month}}$$

Length of Hospital stay is the number of calendar days from the days of patient admission to the day of discharged/died.

Survival data analysis

Time to cure from a certain disease could be a collection of statistical procedures for data analysis that the result variable of interest is time until a happening occurs. By time, mean years, months, weeks, or days from the start of follow-up of a private until an occurrence occurs (Klein M., 2005).

The Bayesian approach analysis considers the parameters of the model as random variables and requires that prior distributions specified for them and data are considered as fixed. The key ingredients to a Bayesian analysis are the likelihood function, which reflects information about the parameters contained within the data, and also the prior distribution, which quantifies what, is understood about the parameters before observing data.

The prior distribution and likelihood is easily combined to make the posterior distribution, which represents total knowledge about the parameters after the info are observed (Christensen R., 2011).

Since survival models are generally quite hard to suit, thanks to the presence of complex censoring schemes, so we apply the tactic of Bayesian with the Gibbs sampler and other MCMC techniques, for fitting complex survival model is fairly straightforward, and availability of software eases the implementation greatly.

Additionally, MCMC sampling enables us to form exact inference for any sample size without resorting to asymptotic calculation (Wioletta G., 2013). A Bayesian method usually requires less sample data to attain the identical quality of inferences than the strategy supported sampling theory. In many cases, this is often the sensible motivation for employing a Bayesian method and represents the sensible advantage within the use of prior information.

A Bayesian analysis has additional practical and important benefits (Wioletta G., 2013).

One is that the increased quality of the inferences, provided the prior information accurately reflects the time variation within the parameter(s). Another benefit is that the reduction in testing requirements (i.e., test time or sample size) that usually occurs in Bayesian reliability demonstration test programs Bayesian inference also has several advantages than frequentist methods within the availability and adaptability of model building and data analysis tools.

Survival functions

The survivor function is defined to be the probability that the survival time of a randomly selected subject is greater than or equal to some specified time. Thus, it gives the probability that an individual surviving beyond a specified time (Klein M., 2005).

One of the important quantities in survival analysis is the survival

Table 1: Description of Variables in the Study

	Variables	Coding for Categorical variables		Description
1	Sex	Female= 0	male=1	Sex of children
2	Age	1-11 = 0 12-23 = 1 24-35 = 2	36-47 =3 48-59 =4	Age of children
3	Residence	Rural = 0	Urban =1	Residence of children
4	Season	Autumn =0 Spring = 2	Winter =1 Summer =3	Season of Diagnosis
5	Co-morbidity	yes = 0	No =1	Co-morbidity (CAP complicated)
6	SAM	yes = 0	NO =1	Sever Acute Malnutrition
7	Treatment types	Penicillin =0 Ampicillin = 2	Ceftriaxone =1 Combined =3	Treatment types taken at time of Diagnosis
8	Patients refer status	No = 0	Yes =1	Patient refer status from other health center

function. Let T be a random variable associated with the survival times, t be the specified value of the random variable T and f (t) be the underlying probability density function of the survival time T.

The cumulative distribution function F(t), which represents the probability that a subject selected at random will have a survival time less than some stated value t,

$$F(t) = p(T < t) = \int_0^t f(u)\,du \ , t \geq 0 \quad (1)$$

The survival function gives the probability that a subject will survive past time t. It is given by

$$s(t) = p(T \geq t) = 1 - F(t), t \geq 0 \quad (2)$$

$$f(t) = \frac{d}{dt}F(t) = \frac{d}{dt}(1 - S(t)) = -\frac{d}{dt}S(t) \geq 0 \quad (3)$$

Hazard function

The hazard function h(t) the instantaneous potential for failing at time t, given that the individual has survived up to time t. In contrast to the survivor function, which focuses on failing, the hazard function focuses on not failing, that is, on the event occurring (Klein, 2005).

The hazard function h(t) ≥ 0 is given as:

$$h(t) = lim_{\Delta t \to 0} \frac{P\{\text{anindividualfailsinthetimeinterval}(t, t+\Delta t)\,\text{givensurvivesuntiltimet}\}}{\Delta t}$$

$$= \lim_{\Delta t \to 0} \frac{p(t \leq T \leq t + \Delta t / T \geq t)}{\Delta t}$$

By applying the theory of conditional probability and the relationship in equation (2) above, the hazard function can be expressed in terms of the underlying probability density function and the Survivor function becomes

$$h(t) = \frac{f(t)}{s(t)} = -\frac{d}{dt}\ln S(t) \quad (4)$$

The corresponding cumulative hazard function H(t) is defined as

$$H(t) = \int_0^t h(u)\,du = -\ln S(t) \quad (5)$$

From the above $S(t) = exp(-H(t))$ and $f(t) = h(t)S(t)$ (6)

Accelerated Failure Time (AFT) models

The Accelerated Failure Time model (AFT) is one of parametric survival model for the analysis of survival time data. Under AFT models we measured the direct effect of the explanatory variables on the survival time instead of hazard. This characteristic allows for an easier interpretation of the results because the parameters measure the effect of the correspondent covariate on the mean survival time (Kalbfleisch J *et al.,* 2002). The accelerated failure-time model is defined by the relationship: $S(t/X) = S_0\{t * exp(\beta tX)\}$ for all X The natural logarithm of the survival time $Y = log(T)$ is modelled. This is the natural transformation made in linear models to convert positive variables to observations on the entire real line.

A linear model is assumed for Y;

$$Y = logT = \mu + \beta_1 X_1 + \cdots + \beta_p X_p + \sigma W$$

$$Y = \beta^t X + \sigma W$$

Where $\beta = (\beta_0, \beta_1, \ldots, \beta_k)$ are parameters of a px1 vector

$\sigma = \frac{1}{\sqrt{\tau}}$ is scale parameter

W= is an error term

The commonly used distributions for W are extreme value, normal and logistic, this leads to Weibull, log-normal and log-logistic models for T respectively. These distributions are appropriate distributions for analyzing the time to event data in this study. We need the survivor function for an individual with event time T and covariate information X, that is, the survival function when $T \sim AFT(FW, \beta, \tau / X)$.

$$S\left(t/x, \beta, \tau\right) = P(T > t \mid X, \beta, \tau) \quad = 1 - FW\left[\left(\log(t) - X^t\beta\right)\sqrt{\tau}\right]$$

Let the precision parameter be denoted by, $\tau = \frac{1}{\sigma^2}$, $\sigma = \frac{1}{\sqrt{\tau}}$ and $\sqrt{\tau} = \frac{1}{\sigma}$, then the survival function, density function and hazard functions are written as

$$S(t \mid X, \beta, \tau) = 1 - Fw\left[\left(\log(t) - X^t\beta\right)\sqrt{\tau}\right] \quad (8)$$

$$f(t|x, \beta, \tau) = \frac{\sqrt{\tau}}{t} f_w\left[\left(\log(t) - X^t\beta\right)\sqrt{\tau}\right] \quad (9)$$

$$h(t|x, \beta, \tau) = \frac{\sqrt{\tau}}{t} h_w\left[\left(\log(t) - X^t\beta\right)\sqrt{\tau}\right] \quad (10)$$

Parametric Accelerated Failure Time (AFT) models (Collett D., 2003)

RESULT AND DISCUSSION

This study included a complete of 345 under-five pneumonia patients fulfilling the inclusion criteria at Menz Gera Mehalmeda Hospital. Summary results for covariates included during this study are presented below.

In *Table 2* beyond the overall of 345 patients of pneumonia included within the study, 38.56% of the patients were female and 61.44% male. Among those patients by considering sex, the death proportion for female is 10.99% which is not up to that of male patients which is 22.07%. Considering age groups included within the study total sample of patients 43.64%, 30.08%, 13.56%, 7.2% and 5.51% of patients were from age bracket 1-11, 12-23, 24-35, 36-47 and 48-59 respectively and also the death proportion for the cohort were 19.49%, 19.72%, 12.5%, 5.88% and 23.08% respectively.

Of the whole patients 63.98% were from country and 36.02% from the urban. Death proportions of patients with residences were 21.85% and 10.59 for rural and concrete respectively. Out of the overall patients, 23.31were at autumn, 27.12% were at winter, 27.12% were at spring and 22.46% patients were at summer. The death proportions of autumn, winter, spring and summer patients were 21.82%, 17.19%, 20.75% and 20.75% respectively.

As shown in *Table 2* above of total patients 57.2% patients were without Co-morbidity and 42.8% were with Co-morbidity. Death proportions of without co-morbidity and with co-morbidity were 13.33% and 13.33% respectively. Similarly in Sever Acute Malnutrition (SAM) case, out of the entire patients there are 91.1% patients without Sever Acute Malnutrition and eight.9% were with Sever Acute Malnutrition. Death proportions among without Sever Acute Malnutrition and with Sever Acute Malnutrition were 13.49% and 61.9% respectively. Among under-five aged children included within the study, 70.34% took treatment type Penicillin, 14.83%took treatment type Ceftriaxone, 5.93% took treatment type Ampicillin and eight.9% patients took treatment type Combination of two and above treatments. The death proportions of patients who took Penicillin, Ceftriaxone, Ampicillin and Combination of two or above were 15.66%, 22.86%, 28.57%, and 19.05%respectively.

Among the patients included within the study 87.71% patients weren't referred from other healthy centers and 12.29% patients were referred from other healthy centers. Death proportion among patients who weren't referred from other hospital and patients who were referred from other consultation room were 16.91% and 24.14% respectively. The mean weight of the patients included within the study was 8.14 with variance of two.39. The mean of Bed Proportion (BOR) at the time of study period was 0.14 with the standard deviation of 0.03. The mean of Patient

Table 2: Descriptive Summary of Pneumonia Data

Variable	Category (codes)	Number of Event (%)	Number of Censored (%)	Total (%)
Sex	Female(0)	10(10.99%)	81(89.01%)	91(38.56%)
	Male(1)	32(22.07%)	113(77.93%)	145(61.44%)
Age	1-11 (0)	20(19.49%)	83(80.58%)	103(43.64%)
	12-23 (1)	14(19.72%)	57(80.28%)	71(30.08%)
	24-35 (2)	4(12.5%)	28(87.5%)	32(13.56%)
	36-47 (3)	1(5.88%)	16(94.12%)	17(7.2%)
	48-59 (4)	3(23.08%)	10(79.92%)	13(5.51%)
Residence	Rural (0)	33(21.85%)	118(78.15%)	151(63.98%)
	Urban (1)	9(10.59%)	76(89.41%)	85(36.02%)
Season of Diagnosis	Autumn (0)	12(21.82%)	43(78.18%)	55(23.31%)
	Winter (1)	11(17.19%)	53(82.81%)	64(27.12%)
	Spring (2)	8(12.5%)	56(87.5%)	64(27.12%)
	Summer (3)	11(20.75%)	42(79.25%)	53(22.46%)
Treatment types taken by patients	Penicillin (0)	26(15.66%)	140(84.34%)	166(70.34%)
	Ceftriaxone (1)	8(22.86%)	27(77.14%)	35(14.83%)
	Ampicillin (2)	4(28.57%)	10(71.43%)	14(5.93%)
	Combined (3)	4(19.05%)	17(80.95%)	21(8.9%)
Co-morbidity	No (1)	18(13.33%)	117(86.67%)	135(57.2%)
	Yes (0)	24(13.33%)	77(76.24%)	101(42.8%)
Sever Acute Malnutrition (SAM)	No (1)	29(13.49%)	186(86.51%)	215(91.1%)
	Yes (0)	13(61.9%)	8(38.1%)	21(8.9%)
Patient refer status	No (0)	35(16.91%)	172(83.09%)	207(87.71%)
	Yes (1)	7(24.14%)	22(75.86%)	29(12.29%)

to Physician Ratio (PPhR) at the time of study period was 3.59 with the standard deviation of 1.11. The mean of patient to nurse ratio (PNR) at the time of study period was 1.20 with the standard deviation of 0.37. After the medical cards of pediatric were reviewed among those patients of under-five pneumonia 42 (17.8%) died and 194 (82.2%) were censored.

Univariable AFT analysis

Univariate analysis is used to see the effect of each covariate on survival time before proceeding to the multivariate analysis. The univariate analysis was fitted for each covariate by AFT models using different baseline distributions i.e. Weibull, lognormal,exponential and log-logistic distributions. In all univariate analysis of AFT model sex, residence, comorbidity, Severe Acute Malnutrition (SAM), age and weight were significantly associated with survival time of patients at 5% level of significance.

Multivariable AFT analysis

For survival time of under-five pneumonia patients data, multivariable AFT models of Weibull, log-logistic,exponential and log-normal distribution were fitted by including all the covariates those are significant in the univariate analysis at 10% level of significance. To compare the efficiency of different models, AIC were used. These are the most common applicable criterion to select model. Based on AICa model having the minimum AIC value was preferred. Accordingly, from the table 3 below log-normal AFT model has (AIC=353.12) found to be good for the survival time of pneumonia patients data set from the given alternatives when include all the covariates those are significant in the univariate analysis. All covariates significant in the univariate become significant in the multivariate analysis model. Finally, the effect of interactions terms were also tested and found to be statistically insignificant in multivariable lognormal AFT model at 5% level of significance. The final model covariates were sex, residence, comorbidity, severe acute malnutrition, age and weight. All AFT models and the corresponding AIC and BIC values were displayed in *Table 3* below to compare classical AFT models with different baseline distributions.

From the likelihood ratio test in *Table 4* below, it was implies that the model is significant and log likelihood values of the null model and the full model showed that the model has a significant improvement after the covariates were added in the model.

Interpretation and presentation of the AFT model

The output of the final lognormal AFT model is presented in *Table 5* below. Thus the factors in the lognormal model were interpreted as follows. This output showed that sex, residence, season of diagnosis at Spring and Summer, Co-morbidity, severe acute malnutrition, patient refer status and patient nurse ratio were statistically significant and that shorten survival time of under-five aged children hospitalized with pneumonia in Menz Gera Mehalmeda Hospital.

Interpretation of accelerated failure time model parameters

Based on the above *Table 5* the final models were interpreted using 95% confidence interval and p-value of the estimate of accelerated failure time model. Interpretations of the coefficients of covariates in the final accelerated failure time model were as follows.

Under the lognormal AFT model, when the effect of other factor keep fixed, the estimated acceleration factor for female patient is with (P=0.0430). This indicates that female patients have less survival time than male patients. The acceleration factors for patients whose residence was rural with (P=0.0279). This indicates that patients whose residence was rural had less survival time than patients from urban residence at 5% level of significance.

From table 5 above the estimated acceleration factor for patient age at 1-11, 12-23 and 24-35 with (P=0.0339, 0.0301 and 0.0101) respectively. This implies that patients whose age were(1-1) months, (12-23) months and (24-35) months was less survival time than patients whose age was (48-59)months. The acceleration factor for patients who were suffered co-morbidity was estimated

Table 3: AFT models Comparison

Model type	Log-Likelihood	AIC	BIC
Weibull	-158.20	358.41	431.16
Exponential	-169.35	378.71	447.99
Log logistic	-157.67	357.35	430.09
Lognormal	-155.55	353.12	425.86

Table 4: Assessment of Model Adequacy for Lognormal AFT Model

Loglik(intercept only)	Loglik(model)	Chi-sq.	DF	Sign
-235	-218	34.08	18	0.012

Table 5: Final Multivariable Analysis for lognormal AFT model

Covariates	Categories	Parameter Estimate	Standard Error	95% Confidence interval	Chi-Square	Sign
Sex	female	1.4466	0.7147	[0.0458, 2.8474]	4.10	0.0430
	male	----	----	----	----	----
Age	1-11	7.1849	2.7927	[1.7112,12.6585]	6.62	0.0101
	12-23	3.6380	1.7151	[0.2765,6.9996]	4.50	0.0339
	24-35	3.9623	1.8272	[0.3811,7.5434]	4.70	0.0301
	36-47	-0.427	0.67959	[-2.143,0.132]	0.3949	0.5297
	48-59	----	----	----	----	
Residence	rural	0.7757	0.7176	[-2.1821,0.6307]	1.17	0.0279
	urban	----	----	----	----	----
Co-Morbidity	yes	-0.4393	0.7157	[-1.8421,0.9635]	0.38	0.0430
	No	----	----	----	----	----
SAM	yes	2.8189	0.9505	[0.9559,4.6818]	8.79	0.0030
	No	----	----	----	----	----
Weight		0.5302	0.2302	[0.0790,0.9814]	5.31	0.0213
Intercept		-3.2796	4.1818	[-11.475,4.9165]	1.62	0.0432

Table 6: Bayesian AFT Model Comparison

Model	AIC	BIC	DIC
Exponential	376.885	414.987	376.510
lognormal	347.812	389.378	350.024
log logistic	351.353	392.919	353.197
Weibull	353.242	394.808	354,871

with p-values is small (P=0.0430). This implies that patients who were not suffered co-morbidity had longer survival time than patients who were suffered co-morbidity. The acceleration factor for patients who were suffered severe acute malnutrition was P-values is small (P=0.0030). This indicates that patients who were not suffered severe acute malnutrition had longer survival time than patients who were suffered severe acute malnutrition.

The acceleration factor for weight of patients with P-value (0.0213) this indicates that weight of patients had significant effect on the survival time of patients at 5% level of significance.

MCMC estimation method

The researcher used uniform prior distribution and Inverse gamma distribution for sigma with scale=0.001, shape=0.001 parameters (*Ghassan H., 2013*). In this simulation study of Bayesian inference using MCMC the researcher was used 12,000 Markov Chain samples by fixing the burn-in state at 2,000. This implies the parameters of the covariates were estimated by 2,000 Markov chain sample values, simply using the Markov Chain samples after the burn-in state.

Based on the above *Table 6* lognormal distribution has smallest DIC values. The distribution with small DIC values is the best distribution that fit the data well, Because of this Bayesian lognormal Accelerating failure time model is selected to be the preferable model to analyze the data in Bayesian approach.

Table 7 above shows that the Posterior summary for Bayesian lognormal AFT model parameter Estimates include Monte Carlo error (MC-error), sample Standard Deviation (SD), median and the 95% credible intervals forthose parameters. It can be seen that for those parameter estimates the Monte Carlo error (MC-error) is less than 5% of standard deviation. So researcher can use those parameter estimates for inferential purpose.

Interpretation of bayesian accelerated failure time model parameters

Under the Bayesian lognormal AFT model, when the effect of other factors keep fixed, the M c error for female patient was 0.004 with 95% CrI: [0.1450, 4.1343]. The credible interval for the Bayesian acceleration failure time didn't include zero or on other hand researcher can say that the credible interval for the Bayesian acceleration factor did not include one by exponentiation of the Bayesian acceleration failure time. This indicates that female patients have less survival time than male patients or in the other way male patients survived longer than female patients. The MC error for patients whose residence rural was 0.004 with [95% CrI: [0.3431, 0.6556]. The credible interval did not include zero. This indicates that patients whose residence was rural had less survival time than patients from urban residence that means patients whose residence was urban had longer survived time than patients whose residence was rural at 5% level of significance.

As shown in table 7 the MC error for age of patients at (36-47) months were 0.047with 95% CrI:-[2.3611,18.6638]. The credible intervals did not include zero. This implies that patients who were at (36-47) month had less survival time than patients whose age was at(48-59) months. But patients whose age were at (1-11) months,(12-23) months and(24-35) month survival time were not significantly different from patients whose age were at (48-59) months at 5% level significance. The MC error for patients

who were not suffered other extra disease or comorbidity was 0.005 with [95% CrI: -2.7401,-1.3356].The credible interval did not include zero. This implies that patients who were not suffered other extra disease had longer survival time than patients who were suffered other extra disease or co-morbidity.

The MC error for patients who were suffered severe acute malnutrition was 0.006 with [95% CrI: 1.4762, 6.8797]. The credible interval did not include zero. This indicates that patients who were not suffered severe acute malnutrition had longer survival time than patients who were suffered severe acute malnutrition or in the other ways patients who were not suffered severe acute malnutrition survived longer than that of patients who were suffered severe acute malnutrition at 5% level of significance. The MC errors for weight of patients were 0.004 with [95% CrI: 0.1699, 1.4078]. The credible interval did not include zero. This indicates that weight had significant effect on the survival time of patients at 5% level of significance.

Assessment of convergence

Time Series (History) Plots: are commonly used to assess convergence of the parameter estimates in Bayesian analysis. The WinBUGS package gives the plot with number of iterations on the x-axis and parameter values on the y-axis for each significant parameter. If the plot looks like a horizontal band, with no long upward or downward trends, then researcher have evidence that the chain has converged. For all simulated parameters, time series plot indicates a good convergence since five independent generated chains are mix together or overlapped.

Autocorrelation Plot: It is a test used for convergence of Bayesian analysis. High autocorrelations in parameter chains often signify a model that is slow to converge. For all simulated parameters, the plot of the first 50 lags of five independently generated chains demonstrated good chain mixture indication of convergence.

Density Plot: This is also the statistical techniques to recognize convergence in Bayesian analysis. When coefficients of independent covariates were normal distributed. Then, it indicates that the Markov chain has attained its posterior distribution (*Figures 1* and *2*).

Assessing accuracy of the bayesian survival analysis

The posterior summary estimates by the MCMC algorithm (Gibbs sampler), like posterior mean, standard deviation, Monte Carlo error and credible interval were estimated using SAS software. To assess the accuracy of Bayesian survival analysis, researchers were used Monte Carlo error for each parameter.

Table 7: Posterior Summary for Bayesian Lognormal AFT Model

Parameter	Var	N	Start	Mean	Sd	Mc error	95%crI
Sex	Female	10000	2000	2.068	1.0216	0.004	[0.1450, 4.1343]
	Male			----	----	----	-----
Age	1-11	10000	2000	5.5033	2.8304	0.045	[-0.0237, 10.8578]
	12-23	10000	2000	4.5833	2.6014	0.041	[-0.3886,9.7329]
	24-35	10000	2000	4.8105	2.7362	0.038	[-0.5545, 10.1459]
	36-47	10000	2000	10.139	4.2161	0.047	[2.3611, 18.6638]
	48-59			----	----	----	----
Residence	Rural	10000	2000	-1.3367	1.0372	0.004	[0.3431, 0.6556]
	Urban			----	----	----	----
Co-morbidity	No	10000	2000	-0.6834	1.0399	0.005	[-2.7401,-1.3356]
	Yes			----	----	----	----
SAM	No	10000	2000	4.1220	1.4019	0.006	[1.4762 , 6.8797]
	Yes			----	----	----	----
Weight		10000	2000	0.7939	0.3190	0.004	[0.1699, 1.4078]

Sd=standard deviation, MC error=Mont Carlo error, 95%CrI = 95% credible Intervals.

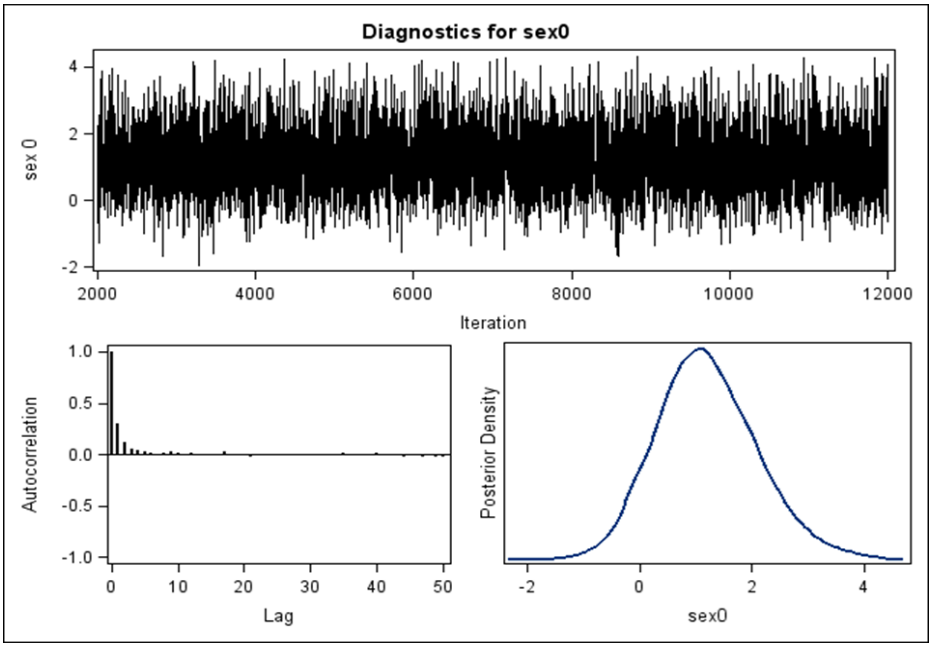

Figure1: Convergence Cheek for Sex and Age of Patients

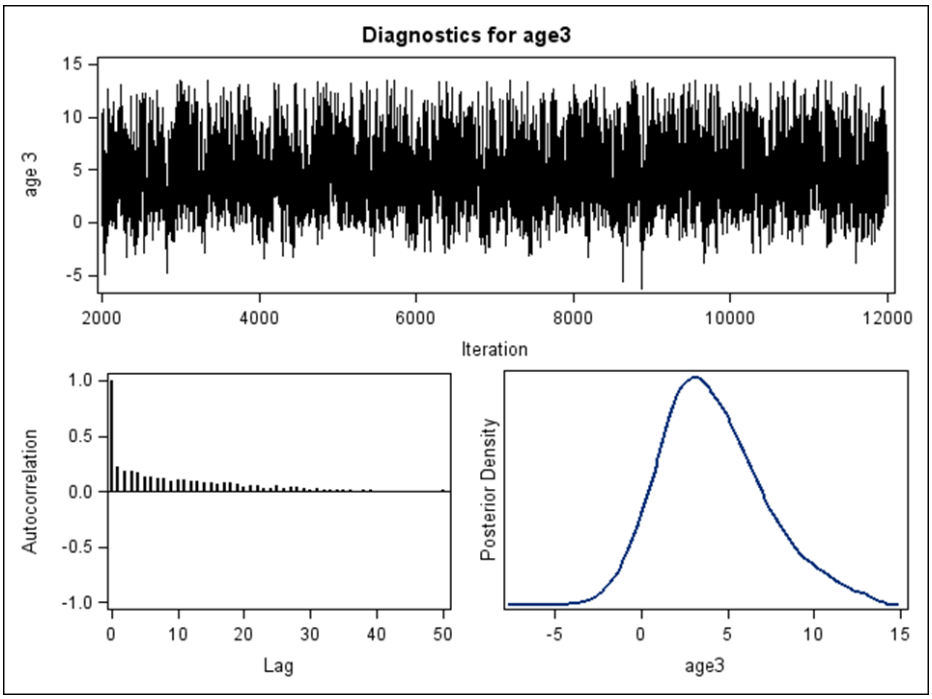

Figure 2: Assessing Accuracy of the Bayesian Survival Analysis

If the MC error value is less than 5% of its posterior standard deviation, then the posterior density is estimated with accuracy. In this study, MC error for each significant variable is less than 5% of its standard deviation. This indicates that convergence and accuracy of posterior estimates are attained and the model is appropriate to estimate posterior statistics.

DISCUSSION

The objective of this study was to identify the risk factors of mortality of under-five pneumonia patients in Menz Gera Mehalmeda Hospital using Bayesian survival analysis. For determining the risk factors of the mortality of under-five pneumonia patients; a total of 236 patients were included in the study out of which (17.8%) were died and (82.2%) were censored.

Descriptive statistics revealed that female patients were more exposed to pneumonia than male patients; this result is in line with other study conducted in JUSH by Firaol B *et al.,* 2017 and in Pakistan by Christa L *et al.,* 2013 and also children in the age group 1-11 months were more exposed than other age groups and this study agrees with study conducted in Sidama Zone Wondo Genet District by Teshome A., 2016. Similarly patients in the rural residence were more exposed than urban residence agrees with study conducted in JUSH by Firaol B *et al.,* 2017 and in China by Feng X *et al.,* 2012. The prevalence of pneumonia in season of spring and winter were higher than other seasons and the results are in line with studies in Hawassa city by Tariku T., 2017 in Malawi by Ellubey R., 2004.

This study focused on Bayesian approaches of survival analysis next to descriptive statistics and the parametric AFT survival model to fit the pneumonia data in Mehalmeda Hospital (Kalbfleisch J *et al.,* 2002). The researchers used different types of the baseline distributions to fit AFT models for pneumonia dataset in Mehalmeda Hospital. The Bayesian analyses were applied on parametric AFT models and the comparison made using DIC values. The Bayesian lognormal AFT model is also selected as the best model in the Bayesian survival analysis based on smaller DIC value (Spiegelhalter D., 2004). Based on the Bayesian lognormal AFT model the study showed that the survival of under-five pneumonia patients was significantly and strongly associated with Sex of children, Residence of children, age of patients at the time of they were admitted to hospital, Comorbidity, Severe Acute Malnutrition and weight of patient . This is consistent with other findings by Firaol B *et al.,* 2017 and by Tariku T., 2017.

The findings of this study was revealed that male patients and patients whose residence was urban had prolonged the timing death of pneumonia while male and patients whose residence was rural had shorten timing death of pneumonia, the study agrees with study conducted at Pakistan (Christa L., 2013 and also with the report of Integrated community case management of childhood illness in South Ethiopia by Solomon *et al.,* 2019. In this study it was found that Patients who were admitted in winter and spring season had shorter survival time and had high risk of dying from CAP as compared with autumn and summer seasons; this result agrees with in southern Israel Hospital by (Lieberman D and Porath A 2005) as reported that there is high incidence of CAP during spring and winter seasons.

Also this study showed that the patients who were suffered comorbidity or any other disease had shorter survival time than patients without comorbidity and also patients suffered Severe acute malnutrition had shorter survival time than that of patients without severe acute malnutrition the studies that support this results were conducted in Pakistan by Duke T *et al.,* 2002 in Malawi by Ellubey R., 2004 in southern Israel Hospital by Lieberman D and Porath A 2005 and the Child Health Epidemiology Reference Group report by Fischer W., 2013. Patients who admitted during Patients to Nurse Ratio (PNR) was had high risk of dying from pneumonia. Since patients in hospital are nurtured by nurses and this has a positive impact on the recovery from their illness. Fortunately, patients who admitted during ratio of patient to nurse is high, has less chance to survive as it is compared to others patients the study agrees with study conducted at Hawassa city by Tariku T., 2017 and in Europe by Andrea D *et al.,* 2017.

The Bayesian survival analysis is started from MCMC simulation of 12,000 samples with burn-in state of 2,000 and using the 2,000 sample for posterior inference using Win BUGS software for simulation and the convergence of the parameters were checked. After 12,000 sample generated the data was converged and the 2,000 sample were used for posterior inference in Bayesian survival

analysis. The MCMC simulations were generated by setting the initial values and burn in state without any criteria, since there is no established method for determining an appropriate number of iterations and burn-in size. Rather, the researchers use a trial-and-error process in which the ultimate goal is to obtain stable parameter estimates that minimize simulation error. This statement confirms with study conducted in USA by Ghassan H *et al.,* 2013. The MCMC simulation in this study was helped to increase the accuracy of the results by narrowing the credible interval and minimizing the standard error, but did not changed the direction of the results this agrees with studies by Hakim E., 2009 and Geir Storvik., 2014

Bayesian survival analysis of this study was showed that smaller standard error and narrow credible interval for all significant parameters. This study is consistent with studies conducted in United Arab Emirates on Overview of Bayesian Approach to Survival Analysis by Cluj-Napoca and Romania 2016. Bayesian lognormal AFT model had narrow credible interval and smaller standard error (MCSE). This implies that Bayesian survival analysis is good to analyze this data set.Thecurrent study is consistent with the studies conducted in Beirut Lebanon by Pascale S *et al.,* 2014.

CONCLUSIONS

This study used survival time of under-five pneumonia patients dataset of those who were registered and treated from September 1, 2002 up to August 30, 2020 years with the aim of investigating the survival rate of under-five pneumonia patients in Mehalmeda Hosptal by applying Bayesian survival analysis. Sample of 345 under-five children hospitalized with pneumonia were used in this study and about (17.8%) of patients were died at the end of study.

To investigate the factors of survival time of under-five pneumonia patients, different types of parametric AFT survival models were applied. parametric AFT models and Bayesian Accelerated Failure Time (AFT) models were fitted. From different types of AFT models fitted using different baseline distributions, lognormal AFT model is selected as the good model in both classical and Bayesian approach investigation based on the classical model comparison criteria using AIC value and Bayesian model comparison criteria using DIC value. In both Approaches lognormal AFT model is selected as the good model to fit the dataset.

The results of both classical and Bayesian lognormal AFT model showed that sex, residence, age, comorbidity, severe acute malnutrition and weight were found to be significant predictors for survival time of patients in Mehalmeda Hospital. Of which patients whose residence was urban, male patients, age of patient at the age of(12-23) months,(24-35) months, (36-47) months and (48-59) months, patients without comorbidity, patients without severe acute malnutrition is prolong timing death of pneumonia patients in Mehalmeda Hospital. Similarly female patients, age of patient at the age of(1-11)months, patients with comorbidity, patients whose residence was rural and patients with severe acute malnutrition were statistically significantly shorten timing of death of under-five pneumonia in Menz GeraMehalmeda Hospital.

Conflict of interest statement

The authors have declared that no competing interests exist.

Creators' commitment

Adimias had made generous commitment to origination and plan, or securing of information, or investigation and translation of the information; Fekade had been engaged with drafting the composition or amending it basically for significant scholarly substance; and had given last endorsement of variant to be distributed.

Subsidizing

The creators have no help or subsidizing to report.

Accessibility of information and materials

The datasets utilized and broke down during the current investigation are accessible from the comparing creator on sensible solicitation. Ethics approval and consent to participate has been approvedby DebreBerhan University.

Morals endorsement and agree to take an interest

Moral freedom ethical Approval was taken from DebreBerhan University; school Post Graduate coordination moral audit board and authority letter was composed by the division of insights to in Mehalmeda hospital North Shewa Ethiopia so as to acquire the information from the emergency clinic before arranging and beginning information assortment. Official letter was given for concerned bodies to conduct the research and afterward privacy of the data was guaranteed from all perspectives.

Consent for publication

Not applicable.

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