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Modeling of Survival of HIV Patients by Stages of Immune Suppression and Opportunisic Infections

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Abstract: Globally, there are many people living with Human Immune Deficiency Virus (HIV), and the rate increases every day. Research has shown that Nigeria is the second largest country with HIV epidemic, as many are living with advanced HIV. People with advanced stage of HIV infection are vulnerable to secondary infections and malignancies, generally termed Opportunistic Infections (OIs). This is because, these infections take advantage of the opportunity offered by a weakened immune system, thereby causing complications in HIV infected persons and causing harm to individuals. The aim of this work is to investigate and model the survival, by stages of immune suppression and opportunistic infections on patients undergoing Antiretroviral Therapy (ART), in a population in South-South Nigeria. 221 Human Immune Deficiency Virus (HIV) patients data obtained from St. Luke's Hospital, Anua, for the period of 2008 to 2017 were used. Four different parametric models, the extreme, lognormal, logistics, log-logistics distributions and nonparametric Kaplan-Meier method were considered in order to carry out modeling of survival, and survival of patients respectively. The models were subjected to life application using lifetime datasets and a test of goodness of fit was made using Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC) criteria. From the results obtained, extremedistribution had the lowest AIC and BIC value, indicating that it is the best parametric model for modeling survival of HIV patients in the hospital. Also, the Kaplan-Meier method indicates that the survival experience of female patients were favorable than male patients.

Keywords: Survival Models, Parametric Models, Kaplan-Meier, Extreme, Lognormal, Logistics, Log-logistics Distributions

1. Introduction

There are currently 35.6 million individuals living with HIV worldwide [1]. Advanced HIV infection may be complicated by opportunistic infections (OIs), malignancies and other consequences of immune dysfunction. Often, OIs constitute the earliest manifestation of HIV infection, denoting significant immunodeficiency [2]. Opportunistic infections leading to significant morbidity and mortality might grossly affect the health and quality of life of people infected with HIV [3]. There is global evidence that the overall incidence of opportunistic diseases and other AIDS defining illnesses (ADIs) increases with the degree of immune suppression resulting from HIV disease progression [4-5].

Nigeria, on her own, has the second largest HIV epidemic in the world [6]. Although HIV prevalence among adults is much less (2.9%) than other Sub-Saharan African countries such as South Africa (18.9%) and Zambia (12.4%), the size of Nigeria's population means 3.6 million people were living with HIV in 2016 [6].

It is estimated that almost two-third of HIV infections in West and Central Africa in 2016 occurred in Nigeria. Together with South Africa and Uganda, the country accounts for almost half of all new HIV infections in Sub-Saharan Africa every year [7]. This is despite achieving a 15% reduction in new infections between 2005 and 2006.

Approximately, 160,000 people died from AIDS-related illnesses (opportunistic infections) in Nigeria in 2016 [8].

Since 2005, the reduction in the number of annual AIDS related deaths have been minimal, indicative of the fact that only 30% of those with a positive diagnosis in Nigeria are accessing antiretroviral treatment (ART) [7].

Unprotected heterosexual sex accounts for 80% of new HIV infections in Nigeria, with the majority of remaining HIV infections occurring in key affected populations such as sex workers [8]. Statistics has shown that six states in Nigeria account for 41% of people living with HIV, including Kaduna, AkwaIbom, Benue, Lagos, Oyo, and Kano [6]. HIV prevalence is highest in southern states than in the northern and eastern states in Nigeria and stands at 5.5%. It is lowest in the southeast (the South-East Zone) where there is a prevalence of 1.8%. There are higher rates of HIV in rural areas (4%) than in urban ones (3%) [6].

Moreover, people with advanced stage of HIV infection are vulnerable to secondary infections and malignancies, generally termed 'opportunistic infections'. This is because, these infections take advantage of the opportunity offered by a weakened immune system. Opportunistic infections are common complications of HIV infection and other ADIs that cause harm in healthy individuals [9].

Some of the most common opportunistic infections include bacterial diseases such as those caused by Mycobacterium Turbaculosuim(TB); Mycobaterium Cholera (Cholera); Pneumonia and Septicaemia (blood poisoning). Protozoan infections, such as: PrenmocystisCarini Pneumonia (PCP), Toxoplasmosis, Isosporiasis, Leishmaniasis and Giardiasis. Fungal infections include Candidiasis, Cryptococcosis (Cryptococcal Meningitis CRM) and Penilliosis. Viral infections associated with HIV/AIDS include Cytomeglalovirus (CMV), Herpes Simplex and Herpes Zorster viruses. Other opportunistic infections include HIV associated malignancies such as Kaposis Sarcoma, Lymphoma and Squamous Cell Carcinoma, others [9]. A healthy uninfected person usually has 800-1200 CD4+T cells/mm^3 of blood. During untreated HIV infection, the number of cells declines. When they fall to 200/mm^3, the person becomes vulnerable to opportunistic infections [10]. Opportunistic infections typically starts manifesting when the CD4 lymphocytes counts of an infected individual declines below critical level, i.e. 800 cells/ml of which the normal value is 1200 cells/ml [9]. When the immune system is severely suppressed in this manner, infections can be fatal, usually resulting to death in less than two years, unless the patient receives specific therapy for HIV infection [9].

Studies by [9-10] on HIV prevalent have reported and also described the spectrum or the incidence of OIs globally, including in India [11], in Nigeria, reported that Oral Candidiasis, Tuberculosis and Dermatitis, constituted 38.2%, 34.2% and 25% of the OIs respectively. He also stated that there was significant difference in frequency of most OIs when the participants of the study were stratified according to gender.

In Nigeria, numerous studies on HIV prevalence exist, but only few focused on describing various opportunistic infections on HIV-infected patients, and none has determined the survival of HIV patients by stages of immune suppression, opportunistic infections, and modeling of survival of HIV patients. So, this paper will focus on survival of HIV patients, by stages of immune suppression, prevalent of opportunistic infections, and modeling of survival among HIV-infected individuals.

2. Material and Methods

St. Luke's Hospital, Anua, Uyo, established about 78 years ago by Catholic Mission is where the secondary data was collected. Data were collected from HIV/AIDS patients' folders from the records department of this tertiary referral hospital. The folders of HIV/AIDS patients were extracted from the library from January 1, 2008 to December 31, 2017. Patient data starts at the date of HIV diagnosis and includes age, gender, date of initiation of HAART, prevalence of opportunistic infections (OIs), date of diagnostic of first opportunistic infection, baseline CD4 count, WHO HIV stage, deaths, time of follow-up where death is the event of interest, were obtained from the folders. There are 221 patients included in the study of which 137 of them died, and 84 were alive. Patients cards where the baseline CD4 count and date of diagnosis of HIV were not recorded. Also, case cards without patient's age and sex clearly written were also excluded. Only properly recorded cards with the given information were extracted for this study.

2.1. Censored Survival Time

Many standard statistical analysis techniques do not apply survival analysisdue to certain aspects of survival data. The primary problem is that some of the subjects or objects will not experience the event called failure or death. That is, some subjects in a study will not fail by the end of the study period. Specifically, censoring is present when we have some information about a subject's event time, but we don't know the exact event time [12]. This incomplete observation of the failure time, t, is referred to as a censored observation. Generally, censoring may occur if the subject does not experience the event of interest before the study ends or if the person is lost to follow-up during the study period. It can also occur if the person withdraws from the study because of death. That is, if death is not the event of interest, or due to other reasons (e.g. adverse drug reactions or involvement in an automotive accident).

2.2. Nonparametric Kaplan-Meier Method

Kaplan and Meier suggested an estimator, a survival function that can be used to estimate a single lifetime indicator [13]. The survival function is given by

$$\hat{S}(t) = \prod_{i=1}^{j} \left(\frac{n_i - d_i}{n_i}\right), j \leq n \quad (1)$$

where, d_i is the number of failures in t_i, n_i is the number of individuals at risk in t_i, and n is the total number of individuals.

The corresponding cumulative hazard function can be

expressed in terms of the Kaplan-Meier survival estimate $\hat{S}(t)$ by:

$$\widehat{H}(t) = -log\left[\prod_{i=1}^{j}\left(\frac{n_i - d_i}{n_i}\right)\right] \quad (2)$$

2.3. Parametric Survival Models

In parametric survival model, the survival time (i.e. the outcome variable) is assumed to follow a known distribution. The parametric models applied in this work are all life time distributions that can be used to model the survival of patients. Their individual probability distribution function, survival function and hazard function are explained in detail below.

2.3.1. Extreme Value Distribution

The extreme value type 1 distribution has two forms. One is based on the largest extreme and the other is based on the smallest extreme. These two forms of the distributions can be used to model the distribution of the maximum or minimum number of the samples of various distributions. For example, if you have a list of maximum river levels for each of the past ten years, you could use the extreme value type 1 distribution to represent the distribution of the maximum level of a river in an upcoming year. This distribution is particularly useful in predicting the chance that an earthquake, flood or other natural disaster will occur.

The probability density function (*pdf*) of the type I (minimum) distribution is

$$f(x) = \frac{1}{\sigma} e^{\frac{x-\mu}{\sigma}} e^{-e^{\frac{x-\mu}{\sigma}}} \quad (3)$$

μ is the location parameter and σ is the scale parameter. When $\mu = 0$ and $\sigma = 1$, the above equation reduces to the standard Gumbel (minimum) distribution given by

$$f(x) = e^{x} e^{-e^{x}} \quad (4)$$

The general formula for the *pdf* of the type I (maximum) distribution is:

$$f(x) = \frac{1}{\sigma} e^{\frac{x-\mu}{\sigma}} e^{-e^{-\frac{x-\mu}{\sigma}}} \quad (5)$$

When $\mu = 0$, $\sigma = 1$, the above equation reduces to the standard Gumbel (maximum) distribution:

$$f(x) = e^{-x} e^{-e^{-x}} \quad (6)$$

With cumulative distribution function (cdf) given by

$$F(x) = e^{-e^{-x}} \quad (7)$$

2.3.2. Logistic Survival Distribution

This type of distribution is utilized in analysis of parametric survivals, where at the beginning the rates goes radically up and then starts to decrease. The location parameter, μ, is the mean. The scale parameter, σ, where $\sigma > 0$, is proportional to the standard deviation. The probability density function and the hazard function of logistic survival distribution are:

$$f(t) = \frac{e^{-z}}{\sigma(1+e^{-z})^2};\ -\infty \le t \le \infty \quad (8)$$

where $z = \frac{t-\mu}{\sigma}$. The hazard function $h(t)$ is given as

$$h(t) = \frac{1}{\sigma(1+e^{-z})} \quad (9)$$

The corresponding survival function $S(t)$ is given as

$$S(t) = \frac{f(t)}{h(t)} = \frac{(1+e^{-z})e^{-z}}{(1+e^{-z})^2} \quad (10)$$

2.3.3. Log-Logistic Survival Distribution

Log-logistic hazard rate model is obtained if the natural logarithm of survival time t has a logistic density with location parameter $\hat{P}$ and scale parameter λ [14]. The pdf and hazard rate functions of log-logistic are

$$f(t) = \frac{(\hat{P}/\lambda)(t/\lambda)^{\hat{P}-1}}{\left[1+(t/\lambda)^{\hat{P}}\right]^2}, t > 0 \quad (11)$$

$$h\left(t; T - LLogist(\lambda, \hat{P})\right) = \frac{(\hat{P}/\lambda)(t/\lambda)^{\hat{P}-1}}{1+(t/\lambda)^{\hat{P}}} \quad (12)$$

The corresponding survival functions is

$$S(t; T - LLogist(\lambda, \hat{P}) = \frac{1}{1+(t/\lambda)^{\hat{P}}} \quad (13)$$

3. Model Selections

In order to discriminate and select the model that best fit lifetime dataset, two criteria were employed. The criteria include Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC). The AIC criterion developed by [15] is defined by:

$$AIC = -2 \times Loglikelihood + 2(p + k). \quad (14)$$

where p is the number of covariates in the model, and k, the number of parameters in the survival distribution considered. The model with the smaller AIC value is selected as the best model. The Bayesian information criterion by [15] is defined by:

$$BIC = -2 \times Loglikelihood + pLog(n). \quad (15)$$

where p represents the number of covariates in the model, and n represent the number of data points. The main advantage of BIC approximation is that it includes the BIC penalty for larger number of parameters being estimated [16]. The model with the smallest BIC value is chosen as the best model.

4. Applications

4.1. Analysis of Data Using Nonparametric Methods

From the survival estimates of the male and female HIV/AID patients in table 1.0 and 1.1 in the Appendix, a total number of sixty-six (66), and eighteen (18) patients were censored respectively. A total of forty-eight (48)

males, and fifty-four (54) females HIV/AIDS patients experienced the event of interest- death. Using tables 1.0 and 1.1, the following facts will enable the comparison of the survival experiences of male and female HIV patients with OIs.

a) Median survival time: The median survival time can be determined by locating the time, in months, at which the survival is equal to 0.5. Here, none of the survival estimates are exactly 0.5, but it can be seen that in the male group, the survival probability changes from 0.5259 to 0.4940 at 63 months; therefore, the median survival time for the male is 63 months. In the female group, the survival probability changes from 0.5053 to 0.4920 at 80 months. So, 80 months is the median survival time for the female gender.

b) Five-year survival rate: The 5-year or 60 month survival rate for the genders can be determined directly from the survival estimate at 60 months. For the male, none of the survival estimates fall at exactly 60 months, but it can be seen that the survival probability changes from 0.5418 to 0.5259 at 56 and 61 months respectively. Therefore, the 5-year survival rate is 0.5259 or 53%; for the female, the 5-year survival estimate 0.6383 or 64% at exactly 60 months.

c) Mean survival time: The mean of the survival times for the genders can be computed, thus, let $\bar{x}_m$ and $\bar{x}_f$ represent the mean survival time for the male and female gender respectively. For the male, $\bar{x}_m = \frac{2782}{48} = 57.96$, and for the female, $\bar{x}_f = \frac{3466}{54} = 64.19$. Since so many of the time in the female group are censored (66), the true mean survival time for that group is, in reality, higher than 64 months (approximately). The true mean survival time for the male gender is also higher than the computed 57.96 (58 months approximately), since 18 males were censored.

Thus, it can be seen that there is another indication that the survival experience of the female gender is more favorable than the survival experience of the male gender.

Average hazard rate: From the raw data of the male and female gender, another descriptive statistic, the average hazard rate, can be used to compare the survival experience by gender. This statistic is a measure of non-survival potential rather than survival. A group with a higher average hazard rate will have a lower probability of survival than a group with a lower average hazard rate. The average hazard rate, designated h_m and h_f for the male and female patients respectively, is gotten by dividing the number of subjects who do not survive by the sum of the observed survival times. For the male, $h_m = \frac{48}{2782} = 0.01725$, and for the female, $h_f = \frac{54}{3466} = 0.01558$.

It can be seen that the average hazard rate for the male is higher than for the female, indicating a smaller chance of survival for male patients.

4.2. The Kaplan-Meier Survival and Hazard Function

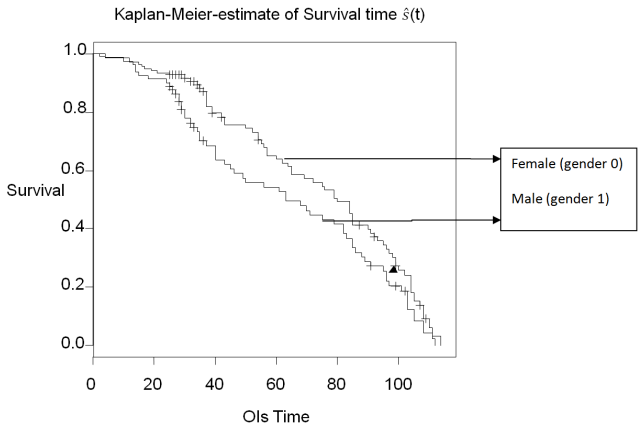

Figure 1. *Kaplan-Meier survival curve showing median survival time and 5-year (60 months) survival rates.*

Figure 2 below, shows the hazard rates of males and females patients. The curve indicates that the hazard rate for the male is higher than the hazard rate for the female.

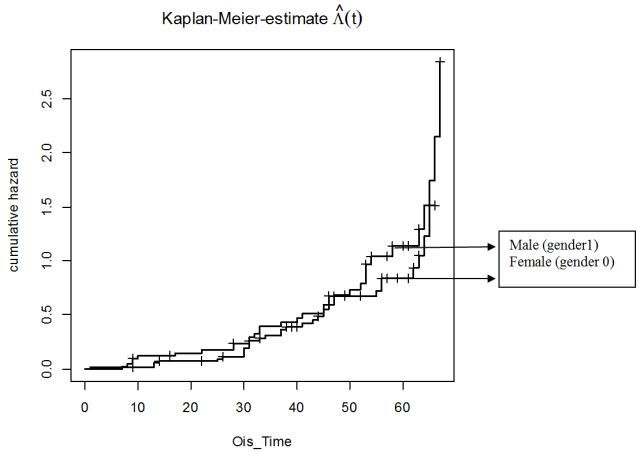

Figure 2. *Kaplan-Meier cumulative hazard curve showing the hazard rates of male and female patients.*

4.3. Analysis of Data Using Parametric Models

The four parametric models discussed in the previous chapter will be compared in this section to determine the model that fits the data most.

4.3.1. Comparison of Parametric Survival Models

Table 4.3 which is the table of goodness of fit provides the Akaike Information Criteria (AIC), and Bayesian Information Criteria (BIC) values. The best model will be chosen based on the smallest value of AIC and BIC.

Table 1. *Goodness-of-fit criteria for parametric models.*

Models	AIC	BIC
Extreme	1405.557	1415.794
Lognormal	1450.150	1460.394
Logistic	1412.014	1422.194
Log-logistic	1429.605	1439.794

Based on the analysis, the extreme value distribution has the AIC value of 1405.557 and BIC value of 1415.794. The

logistic distribution is second with AIC= 1412.014 and BIC= 1422.194, followed by Log-logistic distribution with AIC= 1429.605 and BIC= 1439.794, and then the Lognormal distribution with the highest values of AIC= 1450.150 and BIC= 1460.394. The results in table 1 have shown that extreme distribution has the least AIC and BIC values than the other parametric models, thus considered to have provided the best fit for the HIV/AIDS patient's data.

4.3.2. Graphical Representation of the Survival Probability Plots of the Four Survival Models

The figures presented in the next pages are the fitted survival probability distributions for each of the parametric models, (i.e. the Extreme distribution, Lognormal distribution, Logistic distribution, and Log-logistic distribution).

From figure 3 to figure 6, the survival probability plot of each of the survival distributions is presented, and the performances of the distributions can be seen.

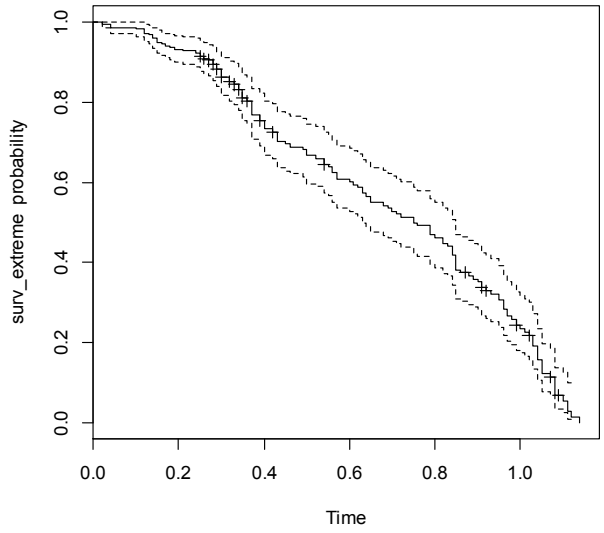

Figure 3. *Survival Plot for the Extreme Distribution.*

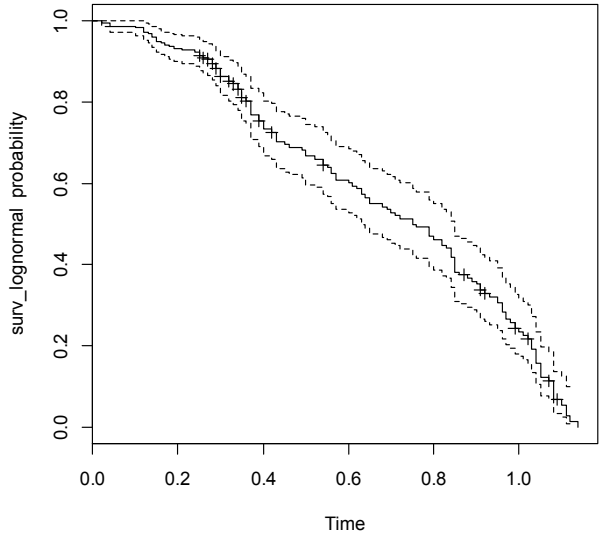

Figure 4. *Survival Plot for the Lognormal Distribution.*

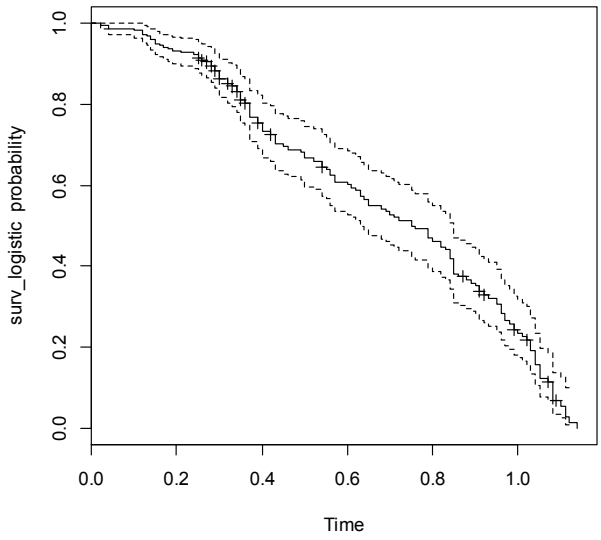

Figure 5. *Survival plot for the Logistic Distribution.*

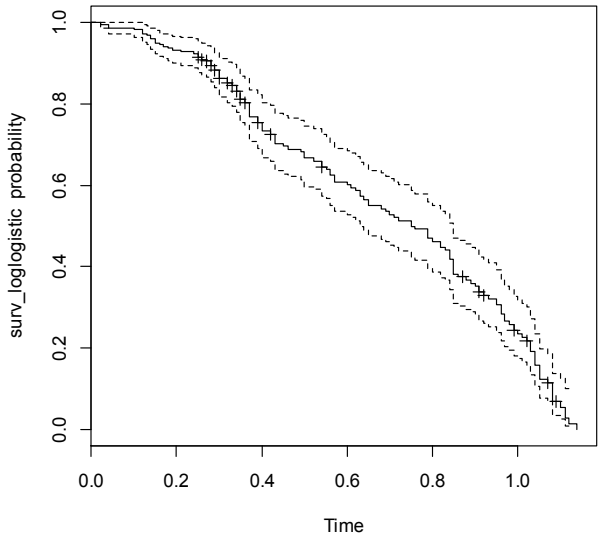

Figure 6. *Survival Plot for the Log-logistic Distribution.*

From figure 1, the movement of the survival probability plot of the Extreme distribution shows a better survival experience, and a better fit to the data, because the step functions shows the highest absolute fit to the data, than the other distributions. This surpassing behavior of the extreme distribution among the other distributions is also justifiable in the result of AIC and BIC earlier presented.

5. Discussion

This research focuses on the survival of HIV patients by stages of immune suppression and opportunistic infections prevalence. Survival analysis methods of nonparametric Kaplan-Meier method and four parametric models were used. The Kaplan-Meier method estimated the survival time or disease-free time from common OIs among study participants by various stages of immune dysfunction, and the best parametric model for the data was chosen using AIC and BIC values as the goodness-of-fit tool.

Based on the Kaplan-Meier estimation of survival, survival experiences of male and female gender were estimated and compared using statistical facts, such as median survival time, 5-year survival rate, mean survival time and average hazard rate. A comparison of the male and female survival experience using the aforementioned statistical facts indicates that the survival experience of female HIV/AIDS patients is more favorable than survival experience of the male counterpart. The Kaplan-Meier survival curve and the cumulative hazard curve were plotted, and based on the graph the survival experience of female patients was seen to be better than the male patients.

Finally, based on the comparison of the four parametric models, the extreme distribution is the best parametric model with the lowest AIC and BIC values, followed by the Logistic model, which indicates that the extreme model is the best parametric model for HIV/AIDS patients.

6. Conclusion and Recommendation

The results show estimates of the survival time of HIV/AIDS patients, and the estimates shows that the survival experience of female patients were favorable than male patients. In terms for the parametric model, the Extreme distribution is the best fitted parametric model for modeling the survival of HIV/AIDS patient. This conclusion is in sync with the findings of [17-19] where a particular distribution was best fitted the data used for their work.

Furthermore, we recommend that other parametric models should be considered for the HIV/AIDS patients data.

Authors Contribution

Edidiong Michael Udofia perfomed presently computational statistical analysis and as well write the paper. Prof. Edith Umeh, participated in analyzing statistical data and supervising the work. The two authors have read and approved final version of the manuscript.

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Appendix

Raw data of HIV/AIDS patients with covariates used for the analysis in R software.

Table 2. *Raw data of HIV/AIDS patients used for the analysis in R software.*

OBS	AGE	CD4 Count	WHO Stage	Number of OIs	Gender	OIs Date of Diagnosis(months)	HIV/AIDS Date of Diagnosis (months)	Censor
1	21	156	4	1	F	36	36	1
2	37	252	2	1	M	30	30	1
3	40	83	3	3	M	35	31	1
4	52	200	3	0	M	85	85	1
5	30	14	3	1	M	103	102	1
6	5	290	2	1	F	42	42	1
7	39	400	3	1	M	28	27	1
8	32	138	3	2	M	35	34	1
9	43	44	3	2	M	29	28	1
10	40	298	4	1	F	34	33	1
11	36	152	3	0	F	37	37	1
12	34	380	2	2	M	97	71	1
13	48	53	3	1	M	79	78	1
14	27	66	4	1	M	14	13	1
15	37	90	2	0	M	4	4	1
16	25	92	4	1	M	24	9	1
17	25	116	3	0	M	45	45	1
18	47	176	3	1	M	63	28	1
19	40	406	4	3	M	37	36	1
20	18	361	2	1	F	39	38	1
21	32	82	3	1	F	37	36	1
22	24	146	3	2	F	99	98	1
23	32	96	3	2	F	79	78	1
24	35	7	4	2	F	91	84	1
25	49	32	3	1	M	89	88	1
26	45	373	2	2	M	70	70	1
27	12	30	3	3	F	111	110	1
28	30	22	3	2	M	111	110	1
29	31	61	3	2	F	98	97	1
30	35	13	4	4	M	82	79	1
31	49	62	4	2	M	105	103	1
32	30	376	3	2	F	17	16	1
33	4	30	4	2	F	84	83	1
34	45	5	2	3	F	93	85	1

OBS	AGE	CD4 Count	WHO Stage	Number of OIs	Gender	OIs Date of Diagnosis(months)	HIV/AIDS Date of Diagnosis (months)	Censor
35	8	56	3	3	M	88	87	1
36	13	91	3	1	F	60	52	1
37	33	18	4	0	F	57	57	1
38	33	261	3	0	F	55	54	1
39	21	85	3	0	M	46	45	1
40	23	80	3	1	F	72	71	1
41	32	253	0	2	F	79	58	1
42	40	201	3	1	M	40	39	1
43	5	640	1	0	F	104	99	1
44	23	207	2	3	F	104	99	1
45	33	194	2	1	F	12	12	1
46	42	79	3	2	M	103	98	1
47	60	444	3	1	M	18	18	1
48	12	134	3	1	F	16	13	1
49	30	32	3	1	F	76	75	1
50	27	72	2	1	F	30	30	1
51	40	111	3	2	M	85	82	1
52	35	80	4	3	M	99	91	0
53	40	72	3	1	F	87	86	0
54	43	32	3	3	M	101	100	1
55	50	222	2	2	M	56	56	1
56	55	13	4	1	M	95	95	1
57	29	33	4	2	F	12	11	1
58	25	60	3	2	M	30	30	1
59	28	59	3	2	M	13	8	1
60	6	296	3	1	F	85	5	1
61	35	215	4	2	F	2	1	1
62	33	162	4	2	F	85	49	1
63	36	110	3	2	F	97	96	1
64	55	79	3	2	F	108	106	1
65	35	205	3	0	F	39	39	1
66	25	84	4	2	F	95	95	1
67	35	184	3	3	F	92	80	1
68	32	92	4	3	F	102	8	1
69	36	80	3	2	M	91	91	1
70	40	85	3	3	F	80	80	1
71	27	240	3	1	F	105	105	1
72	40	319	3	1	F	110	109	1
73	63	16	3	0	F	108	108	1
74	42	218	2	0	M	71	70	1
75	40	236	2	2	M	105	54	1
76	65	210	2	0	M	49	46	1
77	28	370	3	2	F	104	104	1
78	34	56	2	1	M	33	33	1
79	32	35	3	1	M	32	32	1
80	32	150	3	2	F	104	103	1
81	14	292	4	1	F	43	42	1
82	60	161	3	2	M	27	27	1
83	28	38	3	0	M	29	25	1
84	45	134	3	2	M	43	42	1
85	18	130	3	1	F	19	18	1
86	45	143	3	2	M	103	102	1
87	30	82	3	0	F	35	33	1
88	38	161	3	1	F	105	104	1
89	40	207	3	2	F	37	36	1
90	25	59	3	2	F	52	51	1
91	30	73	3	1	F	84	82	1
92	10	23	3	0	M	96	95	1
93	36	37	3	1	F	99	98	1
94	26	130	3	2	F	85	84	1
95	25	129	3	3	M	86	85	1
96	60	176	3	0	F	100	22	1
97	40	27	3	2	F	84	84	1
98	55	33	3	0	M	112	105	1
99	40	146	3	1	M	82	81	1
100	35	161	2	2	F	107	104	1

OBS	AGE	CD4 Count	WHO Stage	Number of OIs	Gender	OIs Date of Diagnosis(months)	HIV/AIDS Date of Diagnosis (months)	Censor
101	37	35	3	2	F	57	56	1
102	26	248	1	0	F	54	54	1
103	37	100	3	2	M	96	88	1
104	32	37	3	3	M	83	83	1
105	50	103	3	3	F	96	95	1
106	31	77	4	0	M	26	25	1
107	28	113	3	1	F	4	3	1
108	46	290	2	1	F	64	63	1
109	36	29	2	1	M	40	15	1
110	40	23	3	4	M	14	14	1
111	25	54	4	4	F	32	31	1
112	12	748	3	3	M	15	6	1
113	40	105	3	2	F	50	50	1
114	38	77	2	0	M	61	61	1
115	32	104	4	1	F	62	61	1
116	28	573	1	1	F	54	54	1
117	30	67	4	1	M	63	62	1
118	57	144	3	1	F	90	54	1
119	40	157	3	1	M	50	49	1
120	53	77	3	1	F	65	64	1
121	49	50	3	1	M	34	28	1
122	64	391	3	1	M	28	27	0
123	40	803	3	1	F	27	26	0
124	20	243	3	2	F	28	27	0
125	42	340	3	2	M	91	27	0
126	35	200	3	1	F	27	27	0
127	32	801	3	0	F	28	27	0
128	24	601	3	1	F	92	27	0
129	28	199	2	1	F	27	27	0
130	30	103	3	2	F	28	27	0
131	63	483	2	0	F	69	69	1
132	34	32	4	1	F	43	43	1
133	25	515	2	0	F	75	75	1
134	40	51	3	1	M	28	27	1
135	42	299	2	0	F	25	24	1
136	34	228	4	3	M	40	39	1
137	39	125	3	1	M	25	24	1
138	24	572	2	0	F	56	53	1
139	54	112	3	4	F	21	18	1
140	37	41	3	1	M	10	10	1
141	20	60	3	1	F	37	36	1
142	31	443	2	3	M	75	42	1
143	30	379	3	2	F	15	14	1
144	41	219	3	1	M	108	107	1
145	35	204	3	2	F	114	107	1
146	38	16	3	1	M	68	67	1
147	54	254	3	1	F	65	63	1
148	56	461	4	1	M	108	107	1
149	28	497	2	1	F	39	25	0
150	25	153	3	1	F	27	6	0
151	42	152	3	1	F	30	29	0
152	21	44	3	4	F	30	29	0
153	30	187	3	2	F	30	29	0
154	30	301	3	1	F	32	28	0
155	50	201	3	1	F	32	28	0
156	30	472	3	1	F	28	28	0
157	29	190	2	4	M	36	28	0
158	40	42	3	1	M	29	28	0
159	25	282	3	1	F	29	28	0
160	26	587	3	1	F	32	28	0
161	25	309	3	3	F	32	28	0
162	46	65	3	1	M	33	28	0
163	28	36	1	0	F	36	35	0
164	25	686	3	0	F	29	28	0
165	45	191	2	1	M	28	27	0
166	34	80	3	3	M	28	27	0

OBS	AGE	CD4 Count	WHO Stage	Number of OIs	Gender	OIs Date of Diagnosis(months)	HIV/AIDS Date of Diagnosis (months)	Censor
167	53	241	3	1	M	28	27	0
168	27	275	3	1	F	28	27	0
169	40	292	3	3	F	30	27	0
170	32	345	3	1	F	29	27	0
171	38	277	3	1	M	29	27	0
172	31	731	2	0	F	29	27	0
173	26	251	3	1	F	28	27	0
174	23	77	3	3	F	28	27	0
175	35	293	3	1	F	107	26	0
176	30	101	2	1	F	28	27	0
177	40	436	3	2	M	27	27	0
178	48	106	3	1	F	28	27	0
179	32	287	3	1	F	107	27	0
180	37	290	3	1	M	32	27	0
181	35	231	3	3	F	28	27	0
182	40	198	2	3	F	29	26	0
183	28	240	3	1	F	27	26	0
184	35	161	3	3	F	39	26	0
185	31	117	2	2	F	34	23	0
186	24	177	4	0	F	28	26	0
187	26	240	3	1	F	26	26	0
188	54	245	3	1	F	28	27	0
189	27	222	3	1	F	99	26	0
190	27	298	3	1	F	27	26	0
191	17	445	4	1	F	109	26	0
192	40	86	3	1	M	28	26	0
193	30	92	3	1	F	26	25	0
194	27	237	3	3	F	29	25	0
195	40	212	3	2	F	107	31	0
196	59	841	3	1	M	102	26	0
197	39	266	3	4	F	26	25	0
198	29	360	3	1	F	26	26	0
199	23	300	3	4	F	26	26	0
200	30	363	3	0	F	54	26	0
201	35	351	3	1	F	29	25	0
202	30	128	3	3	F	26	25	0
203	40	65	3	3	F	42	34	0
204	50	345	3	1	F	29	25	0
205	31	96	2	2	F	26	25	0
206	37	156	2	1	M	26	25	0
207	40	253	3	2	F	33	25	0
208	32	387	3	3	M	27	25	0
209	58	267	3	2	M	25	25	0
210	42	118	2	2	F	29	25	0
211	54	381	3	2	F	27	25	0
212	33	388	3	2	F	27	25	0
213	28	278	2	1	F	25	25	0
214	28	84	2	2	F	30	25	0
215	26	149	3	2	F	35	25	0
216	65	235	3	1	F	25	25	0
217	30	207	2	3	F	25	25	0
218	52	337	3	1	M	26	24	0
219	23	471	3	1	F	25	24	0
220	34	938	2	0	F	26	25	0
221	25	366	3	2	F	26	25	0

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