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KAPLAN MEIER ESTIMATOR AND THE LOG RANK TEST ON SURVIVAL ANALYSIS OF UNDER FIVE MORTALITY PATIENTS OF PNEUMONIA: A STUDY OF STELLA OBASANJO WOMEN AND CHILDREN'S HOSPITAL BENIN CITY, EDO STATE, NIGERIA.

[1]Izomo E.J. and [2]Ogiugo G.O.

Department of Statistics, Edo State Polytechnic Usen. P.M.B 1104, Benin City.

Abstract

The research studied the epidemiological aspects and identified risk factors for incidence and case fatality of Pneumonia among children aged 0 -5 years treated as in-patient at Stella Obasanjo Women and Children Hospital, Benin City in Edo State, Nigeria. Data used were obtained by analyzing hospital records, history, clinical features and laboratory findings at presentation of children 0-5 years managed for pneumonia. The statistical analysis procedure was carried out using survival analysis; a statistical technique that measures the number of subjects survived or saved after intervention over a period of time with the Kaplan-Meier estimator and curves of survival probabilities. Statistical difference between the two regions and sex of the in-patients were compared and checked using the Log-rank test. The median value is 83.42T (1.14 years) with its 95% CI; 2.113-2.169 years and p value = 0.01 Statistically, there is an increase in mortality rate among under five infants (0-5years) overtime as a result of the effect of pneumonia. Since the alternative hypothesis is significantly greater than 1, we conclude that an increase in the risk factor corresponds to an increase in the event hazard which in turn decreases the length of survival. We accept H_R which indicates that the values obtained is greater than 1, hence observed mortality in the hospital is higher than the expected mortality. It is observed that non-functional primary health care centers and inadequate health care services is largely responsible for this fatal disease and this is at variance with the projected achievement of the 4th Millennium Development Goals (MDG4 Target 5). To achieving the United Nations SDGs Sustainable Development Goal 3 which stipulates good health and well-being for all at all ages it is recommended that the Federal Government, State Government's and of course the local Government who is largely responsible for primary health care (PHC) in Nigeria should step up measures aimed at checking possible causes and risk factors of Pneumonia and appropriate measures should be taken in eradicating or reducing these causes to the barest minimum.

***Keywords*:** Survival Analysis, Log-rank test, Kaplan-Meier, Stella Obasanjo Women and Children Hospital, MDG4

1.0 INTRODUCTION

1.1 Background to the Study

Nigeria accounts for one of the nation's globally with high mortality in children by [1]. Mortality refers to a death that occurs within a population at a given period of time. Infant mortality is the number of infants' death occurring within one year after birth per one thousand live births for the given year. Universally, childbirth event attracts celebration but due to the high risk in childbirth delivery encountered by both mother and child, the tragedy of deaths does occur especially during the first few days by [2]Annually, Nigeria records one quarter of babies born dying within their first 28-30 days and before their fifth birthday in [3]. This unhealthy trend has become a matter of great concern, calling for concerted approach from all and sundry.

The Millennium Development Goals (MDG's) by the United Nations global community focuses attention, resources and action on improving the well-being of infants with two of its goals MDG 4 and 5 aimed at reducing childhood mortality rate and maternal mortality ratio by two-thirds and three quarters respectively by the year 2015 by [4]. The incidence of mortality reveals much about a country's population standard of living and health care delivery services [4].

Corresponding Author**:** Izomo E.J., Email: Julius_izomo@yahoo.com, Tel: +2348032278713, +2348056111912

This research examines pneumonia as one of the major killer diseases of infants 0-5 years old using survival analysis. Pneumonia against the natural believe is not caused by exposure to cold weather rather by a common bacteria known as *streptococcus pneumoniae*in [5]. Pneumonia is a leading cause of morbidity and mortality in children 0-5 years old responsible for approximately one of every five under-five mortality cases in Nigeria in [6].

Survival analysis is commonly used in clinical trials and biomedical sciences. It is a statistical method in which the response variable is time. Survival analysis is generally defined as a set of methods for analyzing data where the outcome variable is the time until the occurrence of an event of interest, the event can be death or an occurrence of a disease in [7]. Survival analysis incorporates various statistical methods specific to data on time until an event of interest occurs. While the event is often death, giving rise to the phrase "survival analysis" by [8].

The dependent variable or response is the waiting time until the occurrence of a well-defined event of death in [9]. The conventional end-point in survival analysis is death. Statistical survival analysis shows the magnitude of the expected increase or decline in mortality from clinical trials by [10]. Survival analysis is used to investigate time-to-event outcomes which are common in medical research as they offer more information than simply whether or not an event occurred. Two functions that are dependent on time in survival analysis are the survival function and the hazard function in [11]. They are the key concepts in survival analysis for describing the distribution of event times. The survival function gives for every time, the probability of surviving taking into account cases of survivorship, while the hazard function gives the potential that the event of death will occur per time unit given that an individual has survived up to the specified time in [11]. For efficiency and more robust application in survival analysis, a non-parametric technique known as the Kaplan-Meier survival method will be used in this study. The Kaplan-Meier non-parametric method is widely used in survival analysis than others.

The non-parametric estimator of the survival function known as the Kaplan - Meier method is used to estimate the proportion surviving by any time. It is used to obtain univariate descriptive statistics for survival data by [12]. The Kaplan - Meier estimator method of non-parametric statistics is also called a non-parametric maximum likelihood estimator used for estimating survival probabilities. The important assumption of the Kaplan-Meier survival function is that the distribution of censoring times is independent of the exact survival times and it accommodates no censoring. A data sample is said to be censored when values of the variable are not observed for some of the items in the sample. Patients may have censored survival time if death or recurrence has not yet occurred and this could happen when they drop out of the study or stop attending clinics for follow up. Similarly, certain individuals may drop out from the study or be lost to follow up. Each of these cases is said to be censored while non-censored data are cases where the data entry is complete and the patients completed the treatment. The Kaplan-Meier estimator is assessed by measuring the number of subjects survived or saved after intervention over a period of time. The time starting from a defined point to the occurrence of a given event for example death is called the survival time and the analysis of group data as survival analysis.

To test for overall differences between estimated survival of two or more groups of subjects, such as males versus females, or treated versus untreated, survivals or deaths, the log rank test is used. The log rank test is a method used for comparing the Kaplan - Meier estimate for each group of subjects by [13].

1.2. Justification for the Study

The havoc caused by Pneumonia as a silent killer disease of infants 0 - 5 years old in Nigeria, if not checked will amount to high mortality rate. The level of mortality in any country is an important indicator of the health status of a population and its overall development which tells the quality of life and standard of living in [4]. An increase in mortality rate shows a decline in the health status of a population and this is largely attributable tonon-availability of health care, while a reduction in mortality signifies a tremendous increase in health care delivery services, by [14]. This is a major challenge in the Nigerian health care sector hence a number of preventable diseases lead to death most especially in infants by [14].

It is worrisome to note that Nigeria ranks as one of the 13 countries in the world with the highest infant mortality rate and is still not listed among the 10 countries seen to have made rapid progress in childhood preventable diseases by [15], Nigeria ranked11th in the world infant mortality rate and presently, Nigeria has the 3rd highest infant mortality rate in the world by [16].

Child mortality is associated with Categories of acquired ailments of infectious diseases of which pneumonia has claimed the lives of many before their fifth birthday in [17]. This poses a great danger for our children because with global immunization advocacy this infectious disease can be prevented. The survival of our children basically is dependent on adequate health care facilities and the absence of this factor poses a health risk and hazards to infants who are vulnerable to this diseasesin [6].

Children living in rural settings stand greater risk of dying than those in urban settings due to shortfalls in health programmes. If not given the needed attention by government policies on health care, it will lead to a drastic increase in morbidity and mortality by [18].

In [5] advocates that unclean and unhygienic environments are breeding grounds for germs and bacterial infections which easily contaminate children. In Nigeria most poor people live and give birth in unsafe and unclean environments making their babies more vulnerable to childhood killer diseases contacted from germs and bacterial infections. Poor people give birth to more children than the rich and the natural belief amongst them is that "God Almighty will take care of them" putting them at the probability of survival or death.

Pneumonia usually starts when the germs is breathed into the lungs. The bacteria get into the body either through the mouth or other openings in the body and it contaminates the blood and respiratory apparatus. This makes it hard for the lungs to fight the infection. The likelihood of contacting the disease comes after having a cold or flu. The signs and symptoms include fever, chills, cough, shortness of breath and fatigue. These symptoms are followed by coughing out mucus sputum which is rusty, greenish or tingled with blood, sharp chest pain, shaking, teeth chattering, increased respiratory rate, nausea, vomiting, weakness of the body and diarrhoeain [5]. Based on these challenges, this research introduces a statistical approach to the incidence of pneumonia through the use of survival analysis to ascertain the mortality rate.

1.3. Objectives of the Study

The overall aim of this study is to carryout statistical analysis on the incidence of pneumonia as a major cause of infant mortality in Edo state and proffer possible solutions.

The Specific objectives are to:

(a) analyses available statistical data on the incidence rate of pneumonia in Edo State, Nigeria.
(b) investigate pneumonia occurrence and its impact on infants using the survival analysis to determine the mortality rate in a given time period.
(c)ascertain whether the mortality rate resulting from pneumonia is based on the availability of health care facilities in real life situation.

2.0. LITERATURE REVIEW

Medical researchers are greatly interested in studying the survival of patients. Many researches have been done in the past regarding incidence and mortality in Pneumonia cases of under five children. The need to review some of these previous works and other related topics is necessary as it will add test to this study. In [6] stated that Pneumonia accounted for 23.5% of the 1470 total admission among children one month of five years old and thirty five representing 9.9% of the children died. Children with pneumonia who in addition had concurrent measles infection, heart failure, cyanosis, head nodding and severe under nutrition were at increased risk of death with p-value < 0.05. This research was carried out at Wesley Guild Hospital, Ilesa, Nigeria. A retrospective review of 352 children managed for pneumonia by analyzing hospital records, history, clinical features and laboratory findings at presentation were compared in children who survived and those who died. Binary logistic regression analysis was used to determine the independent predictors of mortality.

Pneumonia is an inflammation of lung tissue due to an infectious agent. Commonly used clinical World Health Organization (WHO) operational definition is based solely on clinical symptoms of cough or difficulties in breathing and tachypnoea. In the developing world, the term lower respiratory tract infection (LRTI) is widely used instead of Pneumonia because of poor access to x-ray and difficulties in radiological confirmation of diagnosis in [13] .Application of survival analysis have gone rapidly and seen wide spread applications in medical and clinical oncology in the last decades and its correct application and presentation is critically relevant to the medical literature. In [13], States that survival analysis are used to investigate time-to-event outcomes which are common in medical research as they offer more information most especially if it is desired to estimate the proportion surviving by any time. Kaplan-Meier can be used and to compare curves from different groups, the log-rank test is used. In [19], Survival analysis must have sufficiently long follow-up durations to capture enough events to reveal meaningful patterns in the data. Survival analysis is a set of statistical procedures for data analysis in the field of medicine.

Survival analysis or more generally, time-to-event analysis refers to a set of methods for analyzing the length of time until the occurrence of a well-defined end point of interest. A unique feature of survival data is that typically not all patients experience the event (e.g. death) by the end of the observation period, so the actual survival times for some patients are unknown. This phenomenon, in [20] is referred to as censoring must be accounted for in the analysis to allow for valid inferences. Moreover, survival times are usually skewed, limiting the usefulness of analysis methods that assume a normal data distribution. Statistical methods for the appropriate analysis of time-to-event data are specifically the Kaplan-Meier estimator and the Log-rank test which will be used in this research study. These methods are by far the most commonly used techniques for data analysis in medical literature. However, a key distinction between survival times and other continuous data is that the event of interest (e.g. death) will usually have occurred only in some but not in all patients by the time the study ends. This is stated by [21] for patients who survive until the end of the study period, or who are lost to

follow-up before the end of the observation period, full survival times are unknown. Instead all that is known is that the survival time is greater than the observation time and this unique feature of survival data is referred to as right censoring. Thus, ignoring censored patients in the analysis, or simply equating their observed survival time (follow-up time) with the unobserved total survival time, would bias the results.

In [22] clinical study, the target population as well as inclusion and exclusion criteria must be clearly defined. A unique feature of survival data is truncation which results from selection bias and refers to subject selection depending on whether or not the event has occurred. Subjects may only be identified for observation at some time point after their respective time of origin. The origin is often when a condition or disease is diagnosed by [8] states that the survival (or survivor) function and the hazard function are fundamental to survival analysis. The survival function describes the probability of surviving past a specified time point or more generally the probability that the event of interest has not yet occurred by this time point. In [21] a research carried out using the Kaplan-Meier method survival function was estimated with 95% confidence interval, censoring was indicated by vertical marks and the number of patients at the risk of different time point is displayed in a graph showing dashed line at a survival probability of .5intersects.The curve represents the estimated median survival time. A hazard rate (or failure rate) is the rate of occurrence of the event during a given time interval. Hazard function describes the instantaneous rate of occurrence overtime, which can conceptually be viewed as the hazard rate during an infinitesimally small time interval. The hazard and survival functions are closely related and can easily be converted to each other. When the hazard rate is high, survival declines rapidly.

In [11] the Kaplan-Meier method estimates the unadjusted probability of surviving beyond a certain time point. A Kaplan-Meier curve shows the estimated survival function by plotting estimated survival probabilities against time. The estimated survival probability is constant between the events. Therefore, the curve is a step-function in which each vertical drop indicates the occurrence of one or more events. Confidence intervals for the survival probabilities can be readily calculated, and confidence bands can be plotted around the survival function. These confidence intervals provide an estimate of the range of plausible values of the survival probability in the population from which the patients are sampled. Often, several Kaplan-Meier curves of different groups (e.g. treatment groups or prognostic factors) are plotted together on the graph, allowing for a visual comparison of the survival probabilities. The Log rank test indicates a significant difference between the survival curves. In a study by [23], the median survival time which is the time when the event has occurred in 50% of the patients or study subjects, is a commonly reported summary statistics for survival time data. This median survival time can be conveniently estimated from the Kaplan-Meier curve as the x-axis (time) value at the point where an imaginary horizontal line at the 50% survival probability on the y-axis crosses the survival curve. Additionally or alternatively, the survival probability at appropriate time points e.g. at 1 – 5 years can also be reported.

Analogous to comparing groups of continuous data using a *t*-test or analysis of variance, the survival curves for 2 or more different groups (e.g. treatments or prognostic factors) can also be compared with hypothesis testing. In a research study by [24], the Log rank test was applied which tests the null hypothesis that there is no difference in the probability of an event at any time point. When reporting, the Log rank test p-value is based on the same assumptions as the Kaplan-Meier survival curve and makes no explicit assumptions about the distribution of the survival curves.

In their retrospective cohort study, [25] sought to identify predictors of long-term survival in patients after lung cancer surgery. In the research study, the log-rank was used to identify covariates that are potentially related to survival. Those covariates that were either considered clinically important displayed a p-value < 0.2 in their Log-rank test. Six factors associated with either longer or shorter overall survival was identified. For example, limited resection was associated with a higher hazard rate and hence shorter survival H_R 1.46; 95%CI, 1.08-1.98; p=0.13 whereas perioperative use of dexamet has one was associated with prolonged survival H_R, 0.70; 95%CI; 0.54 – 0.90; p = 0.006. The researcher also specifically compared patients who received only one drug for treatment. Kaplan-Meier curves were presented for each of the four possible combinations and a log-rank test was used for an unadjusted comparison of the survival curves.

In [26] the Kaplan-Meier method was to estimate median time to achieve adequate analgesia in each treatment group. Median time to adequate analgesia was 8 minutes (95% CI, 1.02 – 2.64; p = 0.042).

Using data on patients who participated in 2 trials across 4 clinical sites for a follow-up analysis by [27] studied effects of supplemental perioperative oxygen on long-term mortality in patients undergoing colorectal surgery. The researchers presented survival curves using Kaplan-Meier estimates. This approach was presumably chosen as it allows for the estimation of an overall H_R estimate and significance across all study sites. No effect of 80% *vs* 30% inspired oxygen was observed on mortality with an over – all estimated H_R of 0.93 (95% CI – 0.72 – 1.20; p-value = 0.57).

In [28] studies on Hypoxemia in hospitalized under-five Nigerian children with Pneumonia asserted that Pneumonia is the foremost cause of death from infectious diseases in under five children. Factors associated with in-hospital mortality were assessed with Kaplan-Meier curves and compared by Log-rank test. Follow-up was censored at 14 days after admission or discharge. The characteristics of patients deceased within 2 weeks (N = 13) were compared with non-deceased patients(N=392).

3.0. MATERIALS AND METHODS

The methodologies used in this research study are the non-parametric estimator of the survival function known as the Kaplan-Meier and the Log Rank test. The Kaplan-Meier method is a non-parametric estimator also called "Product Limit Estimate" which involves computing of probabilities of occurrence of event at a certain point of time. It is widely used in clinical trials because of its versatility in estimating a population survival curve from a sample. In instances where every patient is followed until death, the curve may be estimated simply by computing the fraction surviving at each time. One unique feature of the Kaplan-Meier method is that it allows censoring and non-censoring. That means it allows estimation of survival over time even when patients drop out or are studied for different length of time. It work for each interval as survival probability is calculated by the number of patients surviving divided by the number of patients at risk, died or dropped out.

It is used to estimate conditional probabilities at each time an event occurs and taking the product limit of the probabilities to estimate the survival rate at each point in time.

3.1 The Kaplan-Meier Method

It is a non-parametric survival analysis statistical method used in analyzing data where the outcome variable is time until the occurrence of an event of interest. The event can be death or an occurrence of a disease. The most popular approach with a motivating factor of no censoring accommodation used in survival analysis is the Kaplan-Meier survival function. It is used to estimate conditional probabilities at each time an event occurs and taking the product limit of the probabilities to estimate the survival rate at each point in time.

The Kaplan Meier method is approximately normally distributed with mean s(t) and variance is estimated by the Green wood's estimator formular.

The Kaplan - Meier estimator of the survivorship function or survival probability $s(t) = \rho(T > t)$ is defined by [29]as

$$\hat{S}(t) = \prod_{t_i \le t} \left(1 - \frac{d_i}{R_i}\right) \tag{1}$$

$$\left(1 - \frac{d_1}{R_1}\right) X \left(1 - \frac{d_2}{R_2}\right) X \ldots X \left(1 - \frac{d_j}{R_j}\right) \tag{2}$$

where

t_i= *ith* ordered follow-up time

d_i = number of deaths at *ith* ordered time

R_j = number of censored observation at *ith* ordered time

R_i = number of subjects at risk at *ith* ordered time

Given the Kaplan-Meier survival estimator the Green wood's variance estimator formular is

$$\hat{V}\left[\hat{S}(t)\right] = \hat{S}(t)^2 \sum_{t_{(i)} \le t} \frac{d_i}{R_i (R_i - d_i)} \tag{3}$$

the purpose here is to derive two approximate 95% confidence intervals for *s(t)* for a fixed *t*, or in general, $(1-\alpha)\times 100\%$

Lower = $\hat{S}(t) - 1.96.\hat{S}(t) \sum_{t_i \le t} \sqrt{\frac{d_i}{R_i (R_i - d_i)}}$ (4)

Upper = $\hat{S}(t) + 1.96\hat{S}(t) \sum_{t_i \le t} \sqrt{\frac{d_i}{R_i (R_i - d_i)}}$ (5)

Given the Kaplan - Meier survival estimator and Green wood's variance estimator we can use a Z statistic to compare (test) the probability of survival beyond a certain time, for two groups of subjects.

$$H_o : S_1(t_o) = S_2(t_o) \tag{6}$$

$$H_1 : S_1(t_o) \neq S_2(t_o) \tag{7}$$

Comparing survival function

$$Z = \frac{\hat{S}_1(t_o) - \hat{S}_2(t_o)}{\sqrt{\hat{V}\left[\hat{S}_1(t_o)\right] + \hat{V}\left[\hat{S}_2(t_o)\right]}} \quad (8)$$

Log Rank Test:

It is a confirmatory test used to compare the entire survival function for two groups of subjects. It is one of the most popular tests for comparing two survival distributions. It is more powerful than an analysis based simply on proportions. The Log rank test is a comparing survival function used for each expected observed number of deaths in each group. It is used to compare the total expected ϵ_j death in each group to the total observed death O_j. In [30] it is a type of Chi square test used to test overall difference in survival analysis

$$\varepsilon_{ij} = \left(\frac{R_{1j}}{R_{1j} + R_{2j}}\right)(d_{ij} + d_{2j}) \quad (9)$$

where for each j defined

d_{1j}= number of deaths in group 1
d_{2j}= number of deaths in group 2
R_{1j} = is the number at risk in set group 1
R_{2j} = is the number at risk in set group 2

The Log Rank Test Statistic is

$$\chi^2 = \sum_{i=1}^{2} \frac{(O_1 - E_1)^2}{\hat{v}_1} \quad (10)$$

$$\hat{V}_1 = \sum_{j=1}^{k} \frac{R_{1j}R_{2j}(d_{ij} + d_{2j})(R_{ij} + R_{2j}) - d_{ij} - d_{2j}}{(R_{ij} + R_{2j})^2(R_{ij} + R_{2j} - 1)} \quad (11)$$

$$H_o : S_1(t) = S_2(t) \text{ for all } t \quad (12)$$

$$H_1 : S_1(t) \neq S_2(t) \text{ for some } t \quad (13)$$

Where $S_1(t)$ is the survival of pneumonia; and $S_2(t)$ is the non-survival of pneumonia.

3.2. DATA COLLECTION

The data for this study are secondary data from Stella Obasanjo Women and Children's Hospital Benin City, Edo State, Nigeria. Data collected covers the period of 2007-2016. The data collected are analyzed using the Research methods and the r-statistical software. A first step in survival analysis is often to estimate the survival curve or survival time distribution.

4.0DATA ANALYSIS

The data presented are analyzed based on the estimates of proportion surviving by any time using the Kaplan-Meier methodology. The Log Rank test was used to compare curves from different groups showing the mortality trend in the hospital under consideration.

The data in Table 1 for Stella Obasanjo Women and Children Hospital, Benin City.

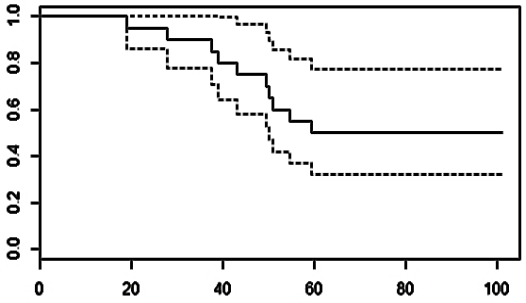
Table 1: Time and incidence table for Stella Obasanjo Women and Children Hospital, Benin City.

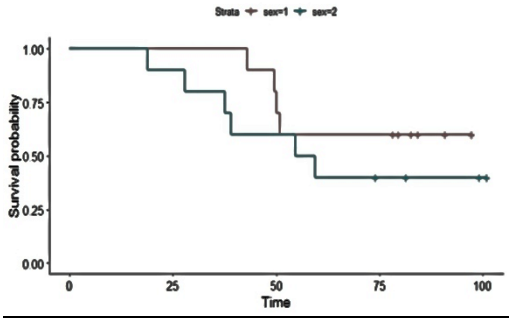
Year	Survival	Death	surv-death ratio (ϖ)	status	Sex	time
2007	205	16	12.81	0	Male	142.439
2008	222	15	14.80	0	Male	123.311
2009	255	16	15.94	0	Male	114.510
2010	224	9	24.89	1	Male	73.326
2011	277	11	25.18	1	Male	72.473
2012	319	11	29.00	1	Male	62.931
2013	211	14	15.07	0	Male	121.090
2014	235	15	15.67	0	Male	116.489
2015	270	11	24.55	1	Male	74.352
2016	206	15	13.73	0	Male	132.888
2007	173	14	12.36	0	Female	147.688
2008	214	17	12.59	0	Female	144.977
2009	252	12	21.00	1	Female	86.905
2010	230	15	15.33	0	Female	119.022
2011	274	12	22.83	1	Female	79.927
2012	313	7	44.71	1	Female	40.815
2013	365	11	33.18	1	Female	55.000
2014	224	7	32.00	1	Female	57.031
2015	219	13	16.85	0	Female	108.333
2016	331	5	66.20	1	Female	27.568

Source: Records Department, Stella Obasanjo Women and Children Hospital, Benin City.(2017)

TABLE 2: SURVIVAL DISTRIBUTION FOR STELLA OBASANJO WOMEN AND CHILDREN HOSPITAL,BENIN CITY.

Time	n.risk	n.event	Survival	std.err	lower.95%.CI	upper.95%.CI
40.81	20	1	0.95	0.0487	0.859	1
55.00	19	1	0.9	0.0671	0.778	1
62.93	18	1	0.85	0.0798	0.707	1
79.90	17	1	0.8	0.0894	0.643	0.996
79.93	16	1	0.75	0.0968	0.582	0.966
86.91	15	1	0.7	0.1025	0.525	0.933
116.48	14	1	0.65	0.1067	0.471	0.897
119.02	13	1	0.6	0.1095	0.42	0.858
12109	12	1	0.55	0.1112	0.37	0.818
144.98	11	1	0.5	0.1118	0.323	0.775





The true survival time follows an exponential distribution with mean time of 90.71T (1.24 years) and a median value 83.42T (1.14years) with its 95% confidence interval 2.113-2.169years.

Figure 1: *The Kaplan-Meier Curve of pneumonia patients in Stella Obasanjo Women and Children Hospital, Benin City.*

The Kaplan-Meier survival probability curve of patients in Stella Obansanjo Women and Children Hospital. Benin City is represented in the solid lines while the dotted lines shows the 95% confidence intervals in figure 1.

Figure2: *Survival time of pneumonia patients for Stella Obasanjo Women and Children Hospital, Benin City with sex as covariate*

[1 = Male 2 = Female]

The orange solid line represents the trend using Male covariates as group 1while the green line represents the female sex covariates as group 2.In this case, the survival probability in under five children as a result of the incidence of pneumonia is higher in the female group 2.

TABLE 3:LOG RANK TEST FOR PATIENTS IN STELLA OBASANJO WOMEN AND CHILDREN HOSPITAL,BENIN CITY.

	N	**Observed**	**Expected**	**(O-E)^2/E**	**(O-E)^2/V**
Sex = Male	10	4	5.55	0.433	1.98
Sex = Female	10	6	4.45	0.540	1.98

Chisquare = 1 on 1 degrees of freedom, p = 0.01

The log rank test in table 3 shows there was statistically significant difference (p=0.01) between Male and Female respondents. Thus, the log rank test of patients in Stella Obasanjo Women and Children Hospital, Benin City, shows the statistically significant evidence of the survival distributions between the male and female respondents are not the same (*p-value =0 .01).*

4.2. RESULTS AND DISCUSSION

The Kaplan-Meier survivorship estimates was used to examine the model fit. The curve checks whether the observed number of events is significantly different from the expected number of events in groups differentiated by risk scores. When reading the curve; horizontal lines represent survival duration for the interval; an interval is terminated by an

event, the height of vertical lines show the change in cumulative probability and censored observations are indicated by tick marks, which help reduce the cumulative survival between intervals.
The median survival time for Stella Obasanjo Women and Children Hospital follows an exponential distribution with mean time of 90.71T (1.24years) and a median value of 83.42T (1.14 years). The log rank shown in Table 3 shows there was significant statistically difference (p =0.01) with its 95% CI at 2.113-2.169yearsbetween male and female patients.
Statistically, there is an increase in mortality among under five infants (0-5 years) over time as a result of the effect of Pneumonia. The H_o Null hypothesis states that there are no differences in survival distribution between the study groups. When the resulting p-value from the Log-Rank test is small Ho should be rejected (H_o< p-value). If H_R – alternate hypothesis is significantly>1, then we can conclude that an increase in the risk factor corresponds to an increase in the event hazard which in turn decreases the length of survival. We accept H_R which indicates that the values obtained is > 1. Hence, observed mortality in both hospitals is higher than the expected mortality.

5.0. CONCLUSION

The ranking of Nigeria as the 11th country with the highest number of newborn deaths in the world ought to give government at all levels and health care givers a serious cause for concern. [31] the report in 8 of the 10 most dangerous places to be born are located in the sub-Saharan Africa were pregnant women are much less likely to receive assistance during delivery due to poverty, conflict and weak institutions with the newborn mortality rate of 29 deaths per 1000 births. The global estimates rank Nigeria as the 11th highest on newborn deaths in the recent multiple indicator cluster survey (MICS) conducted 8th February, 2019.
As a way of building on the successful Millennium Development Goal MDG (UN,2015), the UNGA (United Nations General Assembly, 2015) gave a new contemporary face to the term "Sustainable Development" Goal on the 25th September 2015, the 194 countries of the UNGA adopted the 2030 Development Agenda titled "Transforming our world, the 2030 Agenda for sustainable development".
The UNGA announced the 17 SDG's and 169 targets amongst which are Goal 3. Good health and well-being aimed at ensuring healthy lives and promoting wellbeing for all at all ages in [32].
Scientific research is at the root of every intervention to cure diseases and drug development. As at today, in Nigeria, most expensive drugs are still been imported and more sadden is the fact that no vaccine used for preventing Pneumonia is manufactured here in Nigeria. We have all it takes in terms of human resources and capabilities to get this done locally within our borders. With adequate manpower development in relevant basic sciences and appropriate infrastructural developmentwe can get this resolved locally. Then imagine the huge capital flight we can save, the employment opportunities therein, and the impetus this can offer our economy. Pharmaceutical research should be seen to be above the level of lip service in [32].
In this research study, it was discovered that Pneumonia prevalence among under five children is still on the increase despite global calls for immunizations against childhood killer diseases and infections. Survival analysis using the Kaplan-Meier estimator and the Log-rank comparative test shows that infant mortality is still on the increase and there is no remarkable decline in hazard rate thus negating the chances of survival in the cases of the event of occurrence.
The persistent high maternal and child mortality rate in Nigeria is at variance with theprojected achievement of the 4th and 5th goal of the Millennium development Goals (MDGs) whose target was aimed at reducing the under-five mortality rate by 2/3rdbetween 1990 – 2015 and improve maternal health by reducing maternal mortality ratio by ¾. As a result, Nigeria which constitutes about 1% of the world's population accounts for 10% of theworlds maternal and under five mortality ratesby [16]. Factors associated with the aforementioned problems includes, poor socio-economic development, weak health care system and low socio-cultural barriers to care utilization. In most of our rural centers, there are non-functionalprimary health care centers which has further compounded the issue of adequate health care delivery services.
In this study the incidence of Pneumonia using survival analysis was carefully examined. Survival data are unique in that the research questions essentially involve a combination of whether the event has occurred. Censoring or the incomplete observation of failure times is common in these data such that specific Statistical method was required for an appropriate analysis.
The Kaplan-Meier method which estimates the unadjusted probability of surviving beyond a certain time point and its curves was a useful graphical tool to display theestimated survival function. Log-rank test was used to compare survival curves between the different groups. Survival analysis provided special techniques that are required to compare the risks of death associated with different treatments or groups where the risk changes over time. In doing this, the start and end points were clearly defined and the censored observations noted. The Kaplan-Meier provided a method for estimating the survival curves, while the log-rank test provides a statistical comparison of the two groups and hospitals.
Based on the conclusion arrived at in this study, the following recommendations are made:

1. Child survival as a field in Public Health should be given the needed attention by health care providers.
2. Child survival interventions/mechanism should be spelt out and adequately funded to reducing the high rate of mortality.
3. There is a great need to scale up immunization of children. Immunizing children with vaccines against preventable diseases before the first year of life is lifesaving.
4. Despite significant progress in immunization advocacy and immunization of children in the state and nation Nigeria, a significant percentage of children still do not receive the complete regimen of vaccinations in their first year of life.
5. Pneumococcal and rotavirus vaccines should be administered to infant children with the aim of preventing Pneumonia.
6. Environmental cleanliness should be emphasized to combating germs and bacteria infectious diseases
7. Telemedicine can be introduced. It is a practice that utilizes product of space technology and ICT in health care delivery. Telemedicine makes it possible to treat disease or injury by consultation with a specialist in a remote area by means of a computer or satellite link. Telemedicine health is readily available at all levels of demand irrespective of the remoteness of the location in [32].

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