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Research Article

Survival Analysis of Birth Defect Infants and Children with Pneumonia Mortality in Ghana

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Despite the global decline in infant and child mortality rate, Ghana has failed to record any substantial improvement. In this study, we investigated the effects of some selected risk factors on infant and child survival in Ghana. This study used data from Komfo Anokye Teaching Hospital. 295 infants and children were followed up and time to first occurrence of death was recorded for each infant and child. The life table and Kaplan-Meier methods and the Cox proportional model were used for statistical analyses. The log-rank test statistic was used to test for difference in the survival curves. The results showed that the risk of death among those with birth defects or pneumonia was relatively higher and there is statistically significant difference in the risk of dying between infants with birth defects and those with no birth defects. Also, there is statistically significant difference in the risk of death between children with pneumonia and those with no pneumonia. Our analyses showed that birth defects, preterm birth, accidents, and pregnancy complications are significant risk factors of infant survival. Also, pneumonia, preterm birth, accidents, and diarrhoea are significant risk factors of child survival. Maternal care services should be made available and accessible and mothers should be educated on the importance of maternal care services utilization in order to reduce or mitigate the risk of infant and child mortality. Also, initiating the immunization activities with PCV-13 and Rota-Virus Vaccines, which will reduce Pneumonia and diarrhoea and will improve survival of infants and children under five, should be encouraged or implemented.

1. Background

Infant and child mortality is a global health concern and indicators of infant and child mortality rates measure the well-being of a given country. Infant mortality rate (IMR) is the number of infants dying before reaching one year of age, per 1,000 live births in a given year, whereas child mortality rate (CMR) is the number of children dying before their 5th birthday per 1,000 live births in a given country [1–3].

Almost half of the child mortality (42%) in the world occurs in Africa, and about 25,000 infants who die each day are in Sub-Saharan Africa [1, 4]. Infant mortality rate (IMR) is generally 29 times higher in developing nations compared to developed nations. Globally, infant mortality has dropped significantly by almost 45 percent between 2009 and 2011. However, this progress is not the reality for all countries. Despite much progress in advanced countries, Ghana has failed to make significant progress in checking the rising mortality rate among infants. Currently, about half of the world's infant deaths occur in Ghana, India, Congo, Pakistan, and China [1, 2, 4].

Babies are particularly vulnerable. For instance, more than 40 percent of deaths in infants occur within the first month of life and more than 70 percent occur in the first year of life. In Sub-Saharan Africa, 1 in 8 children dies before reaching the age of 5 relative to 1 in 143 in developed countries [3]. Due to adverse effect of infant and child mortality, the Millennium Development Goal 4 (MDG4) targeted reducing global infant mortality rates by two-thirds between 1990 and 2015 [3]. Global IMR in 1990, 2009, 2010, and 2012 are 12.4 million, 8.1 million, 7.6 million, and 6.6 million, respectively. Between 1990 and 2010, the annual number of deaths in

infants fell to 57 per 1,000 live births in 2010 from 88 per 1,000 births in 1990. To achieve the MDG4, there is a need to know the determinant of infant mortality and implement the appropriate intervention expected from each of the nations of the world. The World Health Organization (WHO) listed malaria, pneumonia, and birth defect as the leading cause of infant and child mortality in Ghana.

In this paper, our aim is to investigate the survival probabilities among infants with birth defects and children with pneumonia in the Ashanti Region of Ghana. We also seek to identify risk factors associated with these survival probabilities [1, 4].

The paper is divided into four sections. This section presents the background of the study. In Methods, we introduce the study setting and describe the study variables and the statistical approaches used in this paper. In Results, we present the results obtained using the statistical approaches implemented to the data. The Conclusion presents summary remarks and conclusions of the study.

2. Methods

In this section, we introduce the study setting and describe the study variables (outcome and explanatory variables) and the statistical methods used.

2.1. Study Setting. This study took place in the Ashanti Region of Ghana. The data were obtained from Komfo Anokye Teaching Hospital, which is the largest hospital in Ghana (located in Kumasi, Ashanti Region). Progress on reducing child mortality has not been sufficient. Since 2008, the number of under-five children deaths has stalled at double the Millennium Development Goal target (82 deaths per 1000 live births in 2011 compared to a target of 40). Malaria is the leading cause of death for children under five. More than half of infant deaths in Ghana happen within the first month of life, and the newborns death rate has not improved in recent years. Malnutrition is a significant indirect cause of child mortality, contributing to one-third of all childhood deaths. Although levels of malnutrition in Ghana have dropped, 23% of children are stunted and 57% are anaemic. Nutrition is particularly poor in Northern Ghana, where almost two in every five children are stunted and more than 80% of children suffer from anaemia. Ghana has excelled in taking action to bring down the under-five mortality rate and as a result has seen a progressive reduction in deaths from 155 to 60 per 1,000 live births between 1990 and 2014. Though this did not quite reach the MDG4 target of 40 deaths per 1,000 live births, it represents an overall reduction of under-five mortality of 58% over the period [1, 4].

Among children under five years, 70% of deaths are caused by infection compounded by malnutrition. Pneumonia has been rated as a prime cause of children under-five year's mortality in Ghana, with an annual death of 4,300 children and 72,000 cases. Pneumonia alone causes about 1.58 million deaths annually of children under five, which is more than the deaths caused by HIV/AIDS, malaria, and measles put together. WHO reported that Ghana, however, has made phenomenal progress over the years in immunization coverage, from a national coverage of 4% in 1985 to 90% in 2012. In the Ashanti Region, the most populous region of Ghana, neonatal mortality rates in 2011 were 35 per 1000 live births, compared with 21 per 1000 live births in the Greater Accra region. The population base of the Ashanti Region makes it a major determinant in many of the health indices of the nation; therefore, in the joint document prepared by Ghana Health Service and UNICEF and presented at the 2012 Health Summit in Accra, the national average for important indices such as maternal and neonatal mortality was adversely affected by the dismal figures from the Ashanti Region, which were higher than the national average [3].

2.2. Study Variables. In this section, we describe the outcome variable and the explanatory variables.

2.2.1. Description of the Outcome Variable. An outcome variable is a variable whose value is being investigated. The value of the outcome variable depends upon other variables known as explanatory variables. In this study, the outcome variable of interest is death among children born with pneumonia (taking value of 1 if death occurs and 0 if no death occurs) or death among infants born with birth defects (taking value of 1 if death occurs and 0 if no death occurs). So the survival time variable records data on time from the occurrence of pneumonia to death among children or time from the occurrence of birth defects to death among infants. We almost never observe the event of interest in all subjects. This will typically occur in a study trial where patients are followed up until the occurrence of the event of interest (e.g., death) or until the end of the period of observation. Also, some patients may withdraw as a result of side effects or be lost to follow-up (a patient may have moved away). In this study, the censoring rule is right censor. That is, we considered such patients that we do not know the time to the occurrence of the event (the survival time) but we only know that it (survival time) will be longer than their time in the study. We call such survival times censored to indicate that the period of observation was cut off before the event of interest occurred.

2.2.2. Description of the Explanatory Variables. We have mentioned in the previous section that the outcome variable depends on explanatory or predictor variables. These variables determine or predict the value or status of the outcome variable. For the child mortality dataset, the explanatory variables are pneumonia (taking a value of 1 if the child has pneumonia or 0 if the child has no pneumonia), preterm birth (taking a value of 1 if the child was born prematurely or 0 if normal birth), accidents (taking a value of 1 if the child suffered from accidence or 0 if no accident), diarrhoea (taking a value of 1 if the child had diarrhoea or 0 if no diarrhoea), national health insurance (taking a value of 1 if the child had insurance or 0 if the child had no insurance), residence (taking a value of 1 if the child is from urban area or 0 if the child is from a rural area), and gender (taking a value of 1 if the child is male and 0 if the child is a female). And age is a continues variable and was measured in weeks. These variables were considered in this study based on expert's advice and preliminary analysis.

For the infant mortality dataset, the explanatory variables are birth defects (taking a value of 1 if the infant has birth defect and 0 if no defect), preterm birth (taking a value of 1 if preterm birth and 0 if normal birth), accidents (taking a value of 1 if the child suffered from an accident and 0 if no accident), pregnancy complications (taking a value of 1 if there are complications and 0 if no complication), national health insurance (taking a value of 1 if the infant had insurance and 0 if the infant had no insurance), residence (taking a value of 1 if the infant is from urban area and 0 if from a rural area), and gender (taking a value of 1 if male and 0 if female).

2.3. Statistical Analysis. In this study, we used four statistical approaches. Firstly, we used the Chi-Square test statistic [5, 6] to assess the significance of association between the outcome variable (death or no death) of interest and explanatory variables. The explanatory variables discussed in the previous section were considered because they are more likely to have influence on infant or child survival probabilities. Secondly, we used the life table and the Kaplan-Meier survival curves to estimate the survival probabilities for infants and children [7–9]. Thirdly, we applied the log-rank test statistic to assess if there is significant difference in the risk of death between children with pneumonia relative to children without pneumonia and also infants with birth defects relative to infants without birth defect. Finally, we used the Cox proportional hazard model to establish the relation between the survival probabilities and the explanatory variables [7, 8, 10–12].

2.3.1. Cox Proportional Hazard Model. The Cox proportional hazards model expresses the hazard as a function of the covariate values defined as

$$h(t) = h_0(t) \exp\left(\beta_1 X_1 + \beta_2 X_1 + \cdots + \beta_p X_p\right), \quad (1)$$

where $\beta_1, \beta_2, \ldots, \beta_p$ are parameter estimates which measure the effect of the risk factors $X_1, X_2, \ldots, X_p$ on the logarithm (1) of the ratio of the death hazard to the baseline hazard function $h_0(t)$. The baseline hazard is the hazard for an individual who has zero values for all the X-variables. The Cox proportional hazard model (1) can also be expressed as

$$\log\left(\frac{h(t)}{h_0(t)}\right) = \beta_1 X_1 + \beta_2 X_1 + \cdots + \beta_p X_p \quad (2)$$

This means that the proportional hazards model may also be regarded as a linear model for the logarithm of the hazard ratio. One major assumption of the model is that if the first individual has a risk of death at the initial time point, that is, twice as high as that of the second individual, then at later times the risk of death is also twice as large. This means that the effects of the different covariates on survival are constant over time.

We used R (version 3.5.2) and STATA (version 13.1) software for the statistical analyses [7, 8, 13–16]. The results from statistical analyses are reported in Section 3. The results of the statistical analyses using the Chi-Square test statistic are reported first, followed by the results of life table, Kaplan-Meier, and then the log-rank test. We then report the unadjusted and adjusted hazards ratios obtained using the Cox proportional hazard regression model [7–10, 12, 13].

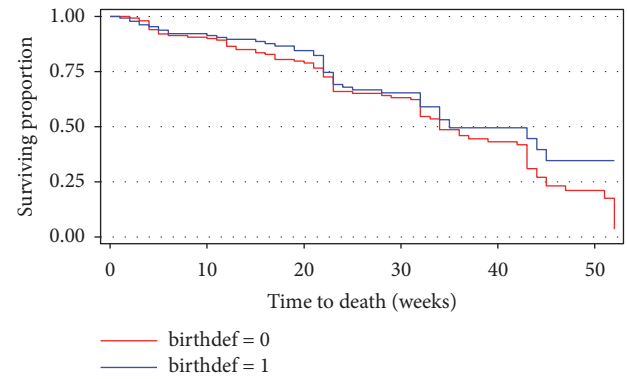

Figure 1: Kaplan-Meier curve showing surviving proportion of the infants with birth defect (birth defect = 1) and infants without birth defect (birth defect = 0).

3. Results

In this section, we present the results using the statistical methods (life table, Kaplan-Meier, and Cox proportional hazard model) for infants and child survival probabilities. We also present the result of the Chi-Square test statistic and the log-rank test.

Table 1 presents the results of the Chi-Square test of association between the dichotomous outcome variable (death or no death), under infant and child mortality, and the explanatory variables. This table shows that infants mortality rate is significantly associated with birth defect, preterm birth, accident, and pregnancy complications. On the other hand, child mortality rate is significantly associated with pneumonia, accident, preterm birth, and diarrhoea.

We now estimate and compare the survival probabilities for infants with birth defects relative to those without birth defect. We also estimate and compare survival probabilities for children with pneumonia relative to those without pneumonia. We estimated and compared these probabilities using the life table and Kaplan-Meier (KM) methods and the log-rank test. Although we have not presented the estimates of the survival probabilities, for infants and children, using the life table method, we will discuss them as well. Figure 1 displays the survival probabilities of infants using the KM method.

The results from the life table and Figure 1 showed that the proportion of infants surviving among the infants with birth defect is low relative to those infants without birth defect. For instance, the probability of surviving, at 20 weeks and above, among infants with birth defect is (67%) lower than that (78%) among infants without birth defect. We test whether there is a statistically significant difference in the survival probability between the two groups (birth defect infants versus infants without birth defect) of infants using the log-rank test statistic. The results from the log-rank test statistic showed that there is no significant difference (Chi-Square = 2.17, p-value = 0.1411) in the survival probability between the two infant groups (birth defect group versus without birth defect group). The median survival time (34 weeks) is the same for infants with birth defect and infants without birth defect. However, at 45 weeks, 75% of the infants

Table 1: A Chi-Square test of association between dichotomous variable (death or no death) and explanatory variables.

Variables	Infant death		Child death	
	0	1	0	1
Birth defect	p-value = 0.0036			
0	73 (45.34)	88 (54.66)	-	-
1	85 (62.96)	50 (37.04)	-	-
Preterm birth	p-value = 0.0002		p-value = 0.0001	
0	66 (40.99)	95 (59.01)	64 (39.02)	100 (60.98)
1	86 (63.70)	49 (36.30)	91 (68.94)	41 (31.06)
Accident	p-value = 0.02068		p-value = 0.0021	
0	75 (46.58)	86 (53.42)	79 (48.17)	85 (51.83)
1	82 (60.74)	53 (39.26)	88 (66.67)	44 (33.33)
Pregnancy complications	p-value = 0001			
0	64 (39.75)	97 (60.25)	-	-
1	89 (65.93)	46 (34.07)	-	-
NHIS	p-value = 0.850		p-value = 0.9294	
0	83 (51.55)	78 (48.45)	85 (51.83)	79 (48.17)
1	72 (53.33)	63 (46.67)	70 (53.03)	62 (46.97)
Residence	p-value = 0.9999		p-value = 0.9999	
0	80 (49.69)	81 (50.31)	83 (50.61)	81 (49.39)
1	68 (50.37)	67 (49.63)	67 (50.76)	65 (49.24)
Gender	p-value = 0.9999		p-value = 0.6673	
0	76 (47.20)	85 (52.80)	78 (47.56)	86 (52.44)
1	63 (46.67)	72 (53.33)	67 (50.76)	65 (49.24)
Pneumonia			p-value = 0.0003	
0	-	-	76 (46.34)	88 (53.66)
1	-	-	90 (68.18)	42 (31.82)
Diarrhoea			p-value = 0.0001	
0	-	-	69 (42.07)	95 (57.93)
1	-	-	94 (71.21)	38 (28.79)

without birth defect are expected to experience the event of interest (death), relative to 34 weeks for infants with birth defects. This implies that it takes shorter time for 75% of the infants with birth defects to die relative to infants without birth defects.

On the other hand, Figure 2 displays the survival probabilities of children under-five years using the KM method. It can be seen that, proportion of children surviving among the children with pneumonia is low relative to those children without pneumonia. That is the probability of surviving, at 71 weeks and above, among children with pneumonia, is (81%) lower than that of (92%) of children without pneumonia. We test for whether there is a statistically significant difference in the survival probability between the two groups (pneumonia versus without pneumonia) of children using the log-rank test statistic. The results from the log-rank statistic showed that there is no significant difference (Chi-Square = 2.77, p-value = 0.0963) in the survival probability between the two infant groups (pneumonia versus no pneumonia). The median survival time (166 weeks) for children without pneumonia is higher than that (156 weeks) for the children with pneumonia. This means that, at 166 weeks, 50% of the children without pneumonia might have experienced the event of interest (death) relative to 50% at 156 weeks (shorter time) for children with pneumonia.

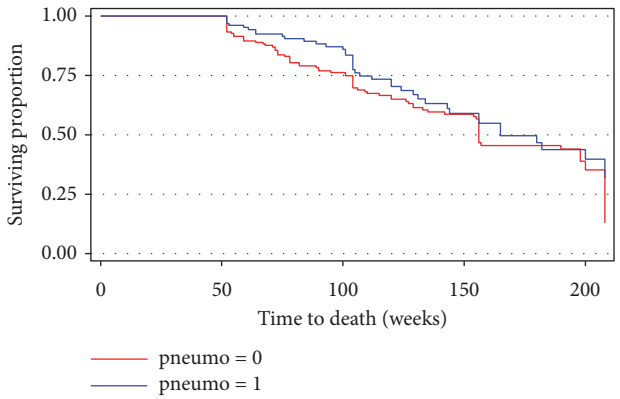

Figure 2: Kaplan-Meier curve showing surviving proportion of the children with pneumonia (pneumonia = 1) and children without pneumonia (pneumonia = 0).

We have now established that the risk of dying among infants with birth defects is higher relative to infants without

Table 2: Parameter estimates from the Cox proportional hazard regression model for infants and children (n = 295).

Variable	Infant death		Child death	
	Unadjusted HR (95% CI)	Adjusted HR* (95% CI)	Unadjusted HR (95% CI)	Adjusted HR (95% CI)
Birth defect (1 versus 0)	0.47 (0.156, 0.781)	0.44 (0.114, 0.772)	-	-
Preterm birth (1 versus 0)	0.49 (0.174, 0.805)	0.43 (0.105, 0.749)	0.59 (0.276, 0.905)	0.46 (0.130, 0.785)
Accidents (1 versus 0)	0.32 (0.013, 0.633)	0.42 (0.098, 0.738)	0.41 (0.104, 0.723)	0.41 (0.102, 0.727)
Pregnancy complications (1 versus 0)	0.60 (0.277, 0.916)	0.57 (0.246, 0.892)	-	-
NHIS (1 versus 0)	0.09 (−0.221, 0.398)	0.07 (−0.247, 0.394)	0.03 (−0.275, 0.338)	0.09 (−0.223 0.409)
Residence (1 versus 0)	−0.07 (−0.376, 0.244)	−0.023 (−0.348, 0.294)	0.11 (−0.192, 0.421)	0.12 (−0.190, 0.438)
Gender (1 versus 0)	−0.24 (−0.549, 0.077)	−0.21 (−0.537, 0.111)	0.06 (−0.245, 0.369)	0.002 (−0.310, 0.3146)
Pneumonia (1 versus 0)	-	-	0.65 (0.344, 0.963)	0.60 (0.282, 0.918)
Diarrhoea (1 versus 0)	-	-	0. 59 (0.280 0.904)	0.57 (0.251, 0.886)
Age (1 versus 0)	0.005 (−0.049, 0.059)	0.04 (−0.014 0.097)	−0.03 (−0.189, 0.124)	−0.03 (−0.184, 0.133)

*HR: hazard ratio and CI: confidence interval.

birth defects. We have also established that the risk of dying among children with pneumonia is higher relative to children without pneumonia. What we have not yet established is the risk factors of surviving/dying among infants and children. To achieve this, we adjust for the effects of the explanatory variable (introduced in Methods) on survival probabilities using the Cox proportional hazard regression model [10, 11, 17]. Table 2 presents the hazard of death among infants and children using the Cox proportional hazard regression model.

For infant's mortality, the results in Table 2 showed that infant survival probability is associated with birth defects, preterm birth, accidence, and pregnancy complications. This means that there is high risk of death among infants with birth defects relative to infants without birth defects and infants who were born prematurely have high risk of death compared with infants of normal birth. Also, infants who were exposed to pregnancy complications are more likely to die relative to those who were unexposed to pregnancy complications. The hazard of death among infants exposed to accidents is high compared with infants who were unexposed to accidents.

For child's mortality, the results in Table 2 showed that child survival probability is associated with pneumonia, preterm birth, accidence, and diarrhoea. That is, there is increased risk of death among children with pneumonia compared with children without pneumonia and there is also high risk of death in children who were born prematurely compared with children of normal birth. We also found that children who were exposed to diarrhoea are more likely to die relative to those who were unexposed to diarrhoea and the hazard of death among children exposed to accidents is high relative to children who were unexposed to diarrhoea.

3.1. Assessing the Cox Proportional Hazard Assumption. The Cox proportional hazards model expresses the hazard as a function of the risk factors. The major assumption of the model is that if the first individual has a risk of death at the initial time point, say, twice as high as that of the second individual, then at later times the risk of death is also twice as large [7]. That is, the effects of the different variables on survival are constant over time. Using the fact that a test for proportional hazards is equivalent to testing for non-zero slope in a regression or Schoenfeld residuals on functions of time, so the test of zero slope is the same as testing that the log hazard ratio function is constant over time [8]. To test for the Cox proportional hazard model's assumption, we applied the *cox.zph* function, in *R software*, on the Cox proportional hazard models for infant and child survivals. The same results can be obtained in STATA software by using *stphtest* command with rank option [13].

For child survival Cox proportional hazard regression model, the results are shown in Table 3. The results showed that all the explanatory variables are constant over time, since they are not statistically significant (p-values > 0.05). This means the variable does not violate the Cox proportional hazard model's assumption and hence the fitted survival model is good and inferences drawn from such model are valid. Furthermore, using the martingale residuals to assess the functional form of the model, more specifically, we test whether the explanatory variables should be in the model and in what form they should be included. We fitted the survival models, excluding each variable considered, and then plotted a lowess smooth of the martingale residuals against each of the variables. Plots of a lowess smooth of the martingale residuals against each variable agree with the results in Table 3 since each of the parameter estimates of the explanatory variables, versus time, has no pattern with time.

For the infant survival hazard model, the results are shown in Table 4. The results showed that all the explanatory variables are constant over time since they are not statistically significant (with p-values > 0.05). It follows that the variable does not violate the Cox proportional hazard model's assumption and hence the fitted survival model is good and inferences drawn from such model are valid. Plots of a lowess smooth of the martingale residuals against each variable agree with the results in Table 4 since each of the parameter estimates of the explanatory variables, versus time, does have any pattern with time. These results illustrated that the constant covariate assumption of the Cox proportional hazard model is satisfied.

Table 3: Child mortality: test of Cox proportional hazard model assumption.

Variables	rho	Chi-Square	p-value
Pneumonia	0.0435	0.28	0.5983
Accidents	0.0680	0.61	0.4339
Preterm birth	−0.0529	0.41	0.5240
Diarrhoea	−0.0746	0.70	0.4018
NHIS	0.0983	1.35	0.2449
Residence	−0.0154	0.03	0.8597
Gender	−0.0181	0.05	0.8305
Age	−0.0536	0.41	0.5217
Global test		4.8	0.8501

Table 4: Infant mortality: test of Cox proportional hazard model assumption.

Variables	rho	Chi-Square	p-value
Birth defect	−0.05838	0.51	0.4754
Preterm birth	−0.13631	2.72	0.0994
Accidents	−0.00094	0.00	0.9914
Pregnancy complications	0.05194	0.36	0.5473
NHIS	−0.02849	0.11	0.7393
Residence	−0.03531	0.18	0.6750
Gender	−0.09760	1.43	0.2322
Age	0.01065	0.02	0.9012
Global test		5.44	0.7093

4. Conclusion

In this paper, we investigated the survival probabilities among infants and children using data from Komfo Anokye Teaching Hospital in Kumasi, Ghana. We estimated and compared survival probabilities of infants with birth defects relative to infants without birth defects using the life table, Kaplan-Meier, and the log-rank methods. These methods were also applied to investigate survival probabilities among children with pneumonia relative to those without pneumonia. We used the Cox proportional hazard model (also known as Cox regression model) to establish a relationship between survival probabilities and the explanatory variables (gender, birth defects, pneumonia, age, pregnancy complications, preterm birth, diarrhoea, residence, accidence, and national health insurance) considered in this study. We also diagnosed the fitted survival models, to the infant and child mortality data, for any violation of the Cox proportional hazard model assumption (effects of different covariates on survival are constant over time) [7, 10]. The data analyses in this paper were carried out using *R* and *STATA* software.

The statistical analyses revealed that infants, with birth defects, who were born prematurely, who were exposed to accidents and pregnancy complications, are less likely to survive longer relative to infants who were unexposed to these risk factors. For children, there was an increased risk of death for children exposed to pneumonia, premature delivery, accidents, and diarrhoea relative to children who were not exposed to these risk factors of child survival. A test for any violation of the Cox proportional hazard model assumption revealed that there is no covariate, included in the survival models, that violated the Cox proportional model assumption of constant covariates effects over time.

The Kaplan and Meier survival function indicates that the surviving proportions decrease over the study period. The survival curve is a step function and indicates that the proportion surviving remains unchanged between events, even if there are some intermediate censored observations. Censor observation is when the time at which the event of interest occurs is unknown (by the researcher or clinician) [7, 12]. It is known that mistaken interpretation of survival curves often involves overinterpretation of the right-hand part of the curve [7, 8]. Survival curves often flatten out after a while, as events become less frequent. Hence, it is incorrect to interpret this flattening as meaningful unless there are many subjects still at risk. The results at the flattened part of the curve are not reliable. This is because the standard errors of the survival proportions increase as the number at risk decreases which results in a widening of the confidence intervals towards the right-hand part of the survival curve to illustrate the uncertainty associated with this part of the curve [7, 12].

Other approaches for assessing the fit of the Cox proportional hazard model are the Cox-Snell residuals to check the overall model fit and martingale and deviance residuals to identify outliers [8, 9]. Medical researchers and clinicians are encouraged to support clinical report/results, based on survival models, with diagnostics tests so that readers of such reports will be able to assess if there is any violation of the assumption of models used.

The life table method calculates survival probabilities after dividing the period of follow-up into time intervals. In some cases, the data may only be available in group form and it is often convenient to summarize the data into groups [7]. However, forming groups involves an arbitrary choice of time intervals and this can be avoided by using a method due to Kaplan and Meier. In the KM method, the data are effectively regarded as groups of a large number of short time intervals, with each interval as short as the accuracy of the data permits. Thus if survival is recorded to an accuracy of one day then time intervals of one-day width would be used.

Data Availability

The authors do not have the ability to make data available.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Abdul-Karim Iddrisu carried out the literature review and statistical analyses and wrote the article. Abukari Alhassan and Nafiu Amidu contributed to the reviewing, proofreading, and interpretation of the results. All the authors have read and approved the final version of the manuscript.

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