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COMPARATIVE SURVIVAL MODELS OF PATIENTS WITH CHRONIC HEPATITIS B: A CASE STUDY AT THE FEDERAL MEDICAL CENTRE, NGURU

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ABSTRACT

Chronic Hepatitis B Virus (HBV) infection remains a major cause of cirrhosis and hepatocellular carcinoma, with a particularly high burden in Nigeria. Identifying prognostic factors and selecting appropriate survival models are essential for improving patient outcomes. This study analyzed 150 patients with chronic HBV managed at the Federal Medical Centre, Nguru, between 2019 and 2024. Survival probabilities were estimated using the Kaplan–Meier method, while the Cox proportional hazards (CPH) model and four Accelerated Failure Time (AFT) models; Exponential, Weibull, Log-logistic, and Lognormal were compared using Akaike (AIC) and Bayesian (BIC) Information Criteria. Covariates included age, gender, METAVIR fibrosis stage, baseline AST and ALT levels, viral load, comorbidities, and antiviral therapy. The Kaplan–Meier curve showed a consistent decline in survival. Model comparison identified the Lognormal AFT model as the best fit (AIC = 71.52; BIC = 101.63), outperforming the CPH and other parametric models. Significant predictors of reduced survival, each one-year increase in age was associated with a 1% reduction in survival time (TR = 0.99, $p < 0.01$), advanced fibrosis (TR = 0.24, $p < 0.001$), elevated AST and ALT ($p < 0.05$), and comorbidities (TR = 0.26, $p < 0.001$). Antiviral therapy was strongly protective, extending survival by more than fourfold (TR = 4.01, $p < 0.001$). The Lognormal AFT model provides the most reliable characterization of survival in this cohort. Early diagnosis, fibrosis staging, and timely antiviral therapy are vital for reducing HBV-related mortality and strengthening long-term outcomes in Northern Nigeria.

Keywords: Chronic Hepatitis B, Survival Analysis, Cox Regression, Accelerated Failure Time Models, Lognormal Model

INTRODUCTION

Chronic Hepatitis B (CHB) infection is a persistent global health challenge, accounting for approximately 296 million chronic cases and nearly 820,000 deaths annually, primarily from cirrhosis and hepatocellular carcinoma (HCC) (World Health Organization, 2021). The disease burden is particularly severe in sub-Saharan Africa, where early childhood transmission and weak screening systems contribute to high endemicity. In Nigeria, pooled prevalence estimates suggest that about 9–10% of the population lives with CHB, ranking the country among the highest-burden nations globally (Adesina et al., 2021). Several recent studies in Nigeria have highlighted the continuing burden of Hepatitis B infection and its clinical variations. For example, Oladele et al. (2020) examined the distribution of ABO/Rhesus blood groups among HBV-positive patients in Lagos, while Pindar, Manu, and Chessed (2023) reported the prevalence of Hepatitis B infection among pregnant women in Gombe State. These findings reinforce the importance of further modelling survival outcomes among HBV patients in different Nigerian populations. Survival analysis provides essential tools for quantifying disease progression and identifying prognostic factors among CHB patients. The Kaplan–Meier estimator offers a simple non-parametric approach to describe survival distributions, while the Cox proportional hazards (PH) model allows for assessing the effect of multiple covariates without specifying a baseline hazard function (Therneau & Grambsch, 2000). These approaches, however, may be limited when the hazard function exhibits specific shapes or when proportional hazards assumptions are not met. Parametric alternatives, particularly those framed under the Accelerated Failure Time (AFT) model, assume explicit probability distributions for survival times and directly model the effect of covariates on survival duration. Commonly applied AFT models include the Exponential, Weibull, Log-normal, and Log-logistic distributions (Lawless, 2003). The Exponential model assumes a constant hazard over time, making it appropriate for diseases with stable risk patterns. The Weibull model generalizes this by allowing for increasing or decreasing hazards, and has been extensively used in liver disease and oncology research (Collett, 2015). The Log-normal model assumes survival times follow a log-normal distribution, which can capture non-monotonic hazard patterns, while the Log-logistic model allows for hazards that initially rise and later decline, making it suitable for diseases with early high-risk phases (Klein & Moeschberger, 2003). Empirical comparisons between Cox and AFT models indicate that parametric approaches may provide better fit and more precise estimates in certain datasets. For instance, Hosseini et al. (2008) demonstrated that Weibull and Log-logistic models yielded superior performance to Cox regression when analyzing stomach cancer data. Similarly, research in HIV and TB cohorts has shown that AFT models often provide more interpretable survival times and improved predictive accuracy (Guo & Carlin, 2004). These models often provide more efficient estimates and better predictive capabilities when the chosen distribution fits the data well. Comparative applications of Cox PH and AFT models have been reported in studies of cancers, cardiovascular diseases, and infectious diseases, showing that parametric AFT models can sometimes outperform semi-parametric Cox models in terms of goodness-of-fit, interpretability of survival times, and prediction accuracy (Collett, 2015; Hosmer, Lemeshow & May, 2008). Despite this, there is a paucity of research

directly comparing these approaches in the context of chronic hepatitis B in Nigeria. This study compares the Cox PH model with four parametric AFT models (Exponential, Weibull, Log-normal, and Log-logistic) to determine the best-fitting survival approach for CHB patients at FMC Nguru. By assessing both model performance and clinical risk factors, the study aims to provide evidence that can improve statistical modeling practice and clinical decision-making for HBV management in Northern Nigeria.

MATERIALS AND METHODS

Research Design

This study compares the performance of non-parametric, semi-parametric and parametric survival models in analyzing risk factors influencing the survival of patients with chronic Hepatitis B (CHB). The data were obtained from medical records of CHB patients who received treatment and follow-up care at the Federal Medical Centre (FMC) Nguru, Yobe State, between 2019 and 2024. The dataset consisted of 150 patient records, including both demographic and clinical variables. Key covariates extracted from the records included: age, sex, viral load, liver biopsy results, alanine aminotransferase (ALT) and aspartate aminotransferase (AST) levels, antiviral therapy status (e.g., Tenofovir use), presence of comorbidities (such as HIV, hypertension, or diabetes), and disease stage (fibrosis or cirrhosis). The primary outcome variable was survival time, defined as the duration (in months) from diagnosis to death or censoring at the end of the study period.

Method of Data Collection

This study utilized data extracted from the medical records of patients with chronic hepatitis B who received care at the Federal Medical Centre, Nguru. The review spanned a six-year period, from January 2019 to December 2024, to ensure a sufficient number of survival events and an adequate follow-up duration for robust analysis. Secondary data were obtained through a structured extraction tool developed to systematically capture demographic, clinical, and survival-related information from patient files. The dataset included patient demographics, clinical characteristics, treatment regimens, and follow-up survival outcomes. Eligibility was restricted to records that met predefined criteria, including a confirmed diagnosis of chronic hepatitis B, initiation of treatment during the study period, and availability of follow-up information. A convenience sampling approach was used to select 150 eligible cases. Each patient was observed from the date of diagnosis or treatment initiation until the occurrence of the outcome of interest (death), loss to follow-up, or the study's end date (December 31, 2024), whichever occurred first. A minimum follow-up period of two years was maintained.

Data Extraction Form

Table 1: Description of Chronic Hepatitis B Data

Section A: Patient Identification (De-identified)	
Variable	Data Entry Format
Patient ID	e.g., P001, P002
Sex	Male / Female
Age at Diagnosis (years)	Numeric
Marital Status	Single / Married / Divorced / Widowed
Occupation	
Section B: Clinical Information	
Variable	Data Entry Format
Date of HBV Diagnosis	DD-MM-YYYY
Date of Treatment Initiation	DD-MM-YYYY
Type of Antiviral Treatment	e.g., Tenofovir, Entecavir
Comorbidities (e.g., HIV, Diabetes)	Yes / No; specify type
Family History of Hepatitis	Yes / No
Baseline ALT Level (U/L)	Numeric
Baseline Viral Load (copies/mL)	Numeric or range
Liver Biopsy or Imaging Result	e.g., Cirrhosis, Fibrosis stage
Adherence Status (if recorded)	Good / Poor / Unknown
Section C: Survival Data	
Variable	Data Entry Format
Last Follow-Up Date	DD-MM-YYYY
Status at Last Follow-Up	Alive / Dead / Lost to Follow-Up
Date of Death (if applicable)	DD-MM-YYYY
Time to Event (in months)	Numeric
Censoring Status	0 = Censored, 1 = Event (death)

Method of Data Analysis

Survival analysis shall be used in analyzing the demographic and clinical dataset, the non-parametric, parametric and semi-parametric will be considered in this research.

Non-Parametric Model: Kaplan–Meier Estimator

Kaplan–Meier (KM) Estimator

Provides a simple way of estimating survival probabilities over time without assuming a specific distribution. A downward step in the curve corresponds to the occurrence of an event (death), while horizontal segments indicate periods with no observed events. To compare survival distributions between groups, the log-rank test was employed. This non-

parametric test determines whether the observed differences in survival curves across subgroups are statistically significant or could have occurred by chance, thereby providing evidence of true variation in survival outcomes.

$$\hat{s}(t) = \prod_{t_i \le t} \left(1 - \frac{d_i}{n_i}\right) \quad (1)$$

Where:
t_i = observed event times
d_i = number of events at time t_i n_i= number at risk just before t_i

Interpretation
The KM curve shows the probability of surviving beyond a given time.
Steeper drops indicate higher risk of death.
The log-rank test can compare survival between groups.

Semi-Parametric Model: Cox Proportional Hazards (PH) Model
The Cox model evaluates the relationship between covariates and the hazard of an event.
The hazard function is defined as:

$$h(t|x) = h_0(t)\exp(\beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_8 x_8) \quad (2)$$

Where:
$h(t|x)$ = hazard function at time t, given covariates x
$h_0(t)$ = baseline hazard function.
$\beta_1, \beta_2, \ldots, \beta_8$ = regression coefficients reflecting the effect of each covariate on the hazard of death

Variables and their Descriptions
The study incorporated both dependent and independent variables:

Dependent Variable
t = Survival time (in months or years) from diagnosis or treatment initiation until death or censoring (alive).
δ = Censoring indicator (1 if the patient died, 0 if censored or alive).

Independent (Covariate) Variables
The independent variables included in the Cox model are as follows:
x_1=Age at diagnosis (years)
x_2=Gender (1 = male, 2 = female)
x_3=ALT levels (alanine aminotransferase, IU/L)
x_4=AST levels (Aspartate Aminotransferase, IU/L)
x_5=HBV DNA viral load (copies/mL)
x_6=METAVIR Fibrosis Stage (1 = advanced fibrosis, 2 = cirrhosis)
x_7=Comorbidities (1 = Yes, 0 = No)
x_8=Antiviral treatment received (1 = tenofovir, 2 = entecavir)
Thus, the model can be expressed as:

$$h(t|x) = h_0(t)\exp(\beta_1 \text{Age} + \beta_2 \text{Gender} + \beta_3 \text{ALT} + \beta_4 \text{AST} + \beta_5 \text{ViralLoad} + \beta_6 \text{METAVIR} + \beta_7 \text{Comorbidities} + \beta_8 \text{Antiviral}) \quad (3)$$

Interpretation
Hazard Ratios (HRs) express covariate effects:
HR > 1: higher risk (shorter survival)
HR < 1: lower risk (longer survival)
HR = 1: no effect
The Cox model assumes:
i. The HRs remain constant over time.
ii. The effect of covariates on the log-hazard is linear.

Parametric Models: Accelerated Failure Time (AFT)
Parametric survival models are often expressed through the Accelerated Failure Time (AFT) framework. Unlike the Proportional Hazards (PH) models that emphasize hazard functions, the AFT models focus directly on survival time. In essence, the AFT model assumes that the effect of covariates is to accelerate or decelerate the time to event by a constant factor. This means that the survival function of an individual with covariates X is equivalent to the baseline survival function evaluated at a rescaled time. The AFT models focus on survival time rather than hazard.

$$\ln(T) = \mu + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_p x_p + \sigma\epsilon \quad (4)$$

Where;
T = survival time
$X_i's$ = independent variable's (covariates)
β′ = are constants to be determined
ϵ = error term whose distribution defines the specific AFT model
σ = is the scale parameter.
μ = is the intercept parameter

Interpretation
coefficients act multiplicatively on survival time. If θj = exp(βj) (the time ratio, TR):
TR > 1: covariate lengthens expected survival time (slower failure)
TR < 1: covariate shortens expected survival time (faster failure)
The AFT survival models considered in this study are: Exponential, Weibull, Log-Normal and Log-logistic survival distributions.

The Exponential AFT Model
The exponential model assumes ε follows an extreme-value distribution or equivalently hazard λ is constant.
Survival function:

$$S(t) = \exp(-\lambda t) \quad (5)$$

Hazard function:

$$h(t) = \lambda\ (constant\ in\ t) \quad (6)$$

under exponential AFT the scale parameter links to λ, the log-time model still holds but implies a constant baseline hazard.

The Weibull AFT Model
The Weibull is the most flexible simple parametric AFT, it nests the exponential and can model monotonic hazard shapes. It's the first parametric choice for many biomedical time-to-event data because of its flexibility and closed-form likelihood.
AFT specification: $\ln(T) = \mu + X\beta + \sigma\varepsilon$ with ε extreme-value.
Survival function:

$$S(t) = \exp(-\lambda t^p) \quad (7)$$

Hazard function:

$$h(t) = \lambda p t^{p-1} \quad (8)$$

If $p > 1$: hazard increases over time
If $p < 1$: hazard decreases over time
If $p = 1$: reduces to Exponential

The Log-Normal AFT Model
The Log-Normal AFT assumes $\varepsilon \sim N(0,1)$ so that ln(T) is normal. It's useful when log-times appear roughly normal or when hazard is non-monotonic (rises then falls); often fits data with a "peak" risk period.
Survival function:

$$S(t) = 1 - \Phi\left(\frac{\ln(t) - \mu}{\sigma}\right) \quad (9)$$

where Φ (·) is the standard normal CDF.

Hazard function: non-monotonic, usually rises then falls.

The Log-Logistic AFT Model

The Log-logistic AFT ε follows logistic distribution on the log scale. Hazard can increase then decrease (non-monotonic), similar to log-normal but with a closed-form survival function.

Survival function:

$$S(t) = \frac{1}{1 + (\lambda t)^{\gamma}} \quad (10)$$

where λ > 0 (scale) and γ > 0 (shape).

Hazard function:

$$h(t) = \frac{\gamma \lambda^{\gamma} t^{\gamma-1}}{1 + (\lambda t)^{\gamma}} \quad (11)$$

Model Selection Criteria

In survival analysis, selecting the most appropriate model is essential for ensuring valid inferences. Several criteria have been developed for this purpose, including those that minimize information loss (Akaike, 1974), maximize posterior probability (Schwarz, 1978), or apply Bayesian approaches such as the Deviance Information Criterion (Spiegelhalter et al., 2002). Among these, the most widely applied are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

The AIC is defined as:

$$AIC = -2\ln(\hat{L}) + k \times p \quad (12)$$

Where:

$\hat{L}$ = maximum likelihood of the fitted model

p = number of estimated parameters

k= penalty constant (usually set to 2)

Similarly, BIC introduces a stronger penalty for model complexity, making it more conservative in selecting models with additional parameters. For this study, both AIC and BIC will be employed to compare competing survival models and identify the best-fitting one.

Justification of the Methods of Analysis

The Cox Proportional Hazards (CPH) model is widely used in survival analysis to assess the influence of covariates on the time to an event, such as death or disease progression. It estimates the relative hazard associated with predictors, making it useful f or identifying risk factors while leaving the baseline hazard function unspecified. However, the CPH model relies on the proportional hazards assumption, meaning that hazard ratios between groups remain constant over time. When this assumption is not valid, the Accelerated Failure Time (AFT) models provide a valuable alternative. Unlike the PH approach, AFT models directly model survival time, interpreting covariate effects as accelerating or decelerating the expected time to event. AFT models are often easier to interpret since regression coefficients represent time ratios, and they tend to be more robust when certain covariates are omitted. Moreover, they are less sensitive to the assumed probability distribution, making them a flexible choice when hazards are not proportional.

RESULTS AN DISCUSSION

Application to Chronic Hepatitis B Data

Table 2: Summary Statistics of Categorical Data for Chronic Hepatitis B

Covariates	Categories	Status		Total
		Censored (%)	Event (%)	
Gender	Male	59(59.0)	41(41.0)	100
	Female	32(64.0)	18(36.0)	50
Marital Status	Single	44(88.0)	6(12.0)	50
	Married	44(45.36)	53(54.64)	97
	Divorced	3(100.0)	0(0.0)	3
Occupation	Student	43(87.76)	6(12.24)	49
	Farmer	14(34.15)	27(65.85)	41
	Civil Servant	17(70.83)	7(29.17)	24
	Housewife	14(48.28)	15(51.72)	29
	Teacher	0(0.0)	1(100.0)	1
	Fisherman	2(66.67)	1(33.33)	3
	Businessman	1(33.33)	2(66.67)	3
METAVIR Fibrosis Stage	Advanced Fibrosis	91(64.08)	51(35.92)	142
	Cirrhosis	0(0.0)	8(100.0)	8
Antiviral	Tenofovir	2(4.65)	41(95.35)	43
	Entecavir	89(83.18)	18(16.82)	107
Comorbidities	Yes	78(92.86)	6(7.14)	84
	No	13(19.70)	53(80.30)	66

Source: Computed using STATA

Table 3: Summary Statistics of Quantitative Data for CHB

Covariates	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Age at diagnosis	150	17	81	5836	38.91	15.384
Baseline AST (U/L)	150	137	365	35565	237.10	44.186
Baseline ALT level (U/L)	150	134	375	36378	242.52	45.458
Baseline viral load (IU/mL)	150	13107	41897	3740375	24935.83	4810.236

Source: Computed using STATA

Model Selection Criterion

Table 4: Results of Model Selection Criterion

Model	AIC	BIC
CPHM	409.73	433.82
Exponential AFT	183.57	210.67
Weibull AFT	84.05	114.15
Log logistic AFT	74.33	104.43
Lognormal AFT	71.52	101.63

Source: Extracted from STATA output

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) was used for model selection.
Rule of thumb: The model with the lowest AIC and/or BIC is considered the best fit to the data.

Cox Proportional Hazard Model Results

Table 5: Cox Proportional Hazard Model for Chronic Hepatitis B Data

Covariates	B	HR	S. E	P-value
Gender	.601	1.824	.353	0.089
Age at Diagnosis	.025	1.025	.012	0.043**
METAVIR Fibrosis Stage	1.146	3.145	.507	0.024**
Baseline AST (U/L)	.014	1.014	.008	0.097
Baseline ALT (U/L)	.011	1.989	.008	0.159
Baseline Viral Load	.000	1.000	.000	0.359
Comorbidities	1.414	4.114	.475	0.003***
Antiviral	-1.47	0.229	.364	0.000***
		Likelihood ratio (θ): $\chi^2 = 76.29$; prob. =0.000***		

Source: Computed using STATA

Model Diagnostics and Assumptions

Test for Proportionality Assumption

Table 6: Proportional Hazard Assumption for Chronic Hepatitis B Data

	Chi-square	P-value
Global test for CPH model	10.56	0.2278

Source: Computed using STATA

The global Schoenfeld residual test (p = 0.2278) indicated that the PH assumption was not violated for the Cox model.

Test for Harrell's C Concordance Statistic

Table 7: Harrell's C Concordance Statistic for Chronic Hepatitis B Data

Harrell's	C = (E + T/2) / P = 0.8450
Somers'	D = 0.6899

Source: Computed using STATA

Table 8: Weibull AFT Model for Chronic Hepatitis B Data

Covariates	B	TR	S. E	P-value
Gender	-0.157	0.854	.078	0.039**
Age at Diagnosis	-0.007	0.993	.013	0.017**
METAVIR Fibrosis Stage	-1.315	0.268	.173	0.012**
Baseline AST (U/L)	-0.002	0.998	.001	0.045**
Baseline ALT (U/L)	-0.002	0.998	.001	0.284
Baseline Viral Load	0.000	1.001	.000	0.409
Comorbidities	-1.356	0.257	.092	0.007***

Covariates	B	TR	S. E	P-value
Antiviral	1.36	3.896	.134	0.000***
		Likelihood ratio (θ): $\chi^2 =$ 76.94; prob. =0.000***		

Source: Computed using STATA

Table 9: Log logistic AFT Model for Chronic Hepatitis B Data

Covariates	B	TR	S. E	P-value
Gender	-0.091	0.913	.076	0.027**
Age at Diagnosis	-0.008	0.992	.033	0.013**
METAVIR Fibrosis Stage	-1.462	0.231	.221	0.001***
Baseline AST (U/L)	-0.004	0.996	.002	0.049**
Baseline ALT (U/L)	-0.004	0.996	.002	0.038**
Baseline Viral Load	0.000	1.001	.000	0.769
Comorbidities	-1.334	0.263	.073	0.001***
Antiviral	1.39	4.014	.125	0.000***
		Lratio (θ): $\chi^2 = 87.14$; prob. =0.000***		

Source: Computed using STATA

Table 10: Lognormal AFT Model for Chronic Hepatitis B Data

Covariates	B	TR	S. E	P-value
Gender	-0.119	0.887	.071	0.013**
Age at Diagnosis	-0.008	0.992	.031	0.005***
METAVIR Fibrosis Stage	-1.444	0.235	.217	0.001***
Baseline AST (U/L)	-0.003	0.997	.002	0.041**
Baseline ALT (U/L)	-0.004	0.996	.002	0.035**
Baseline Viral Load	0.000	1.001	.000	0.871
Comorbidities	-1.336	0.262	.069	0.001***
Antiviral	1.39	4.014	.119	0.000***
		Likelihood ratio (θ): $\chi^2 = 87.64$; prob. =0.000***		

Source: Computed using STATA

Kaplan-Meier Survival Curve Analysis for Chronic Hepatitis B Data

The Kaplan-Meier survival analysis was conducted to estimate and visualize the survival experiences of chronic Hepatitis B patients over the follow-up period. The resulting survival curves represent the probability of survival over time and provide a graphical summary of patient outcomes across different subgroups.

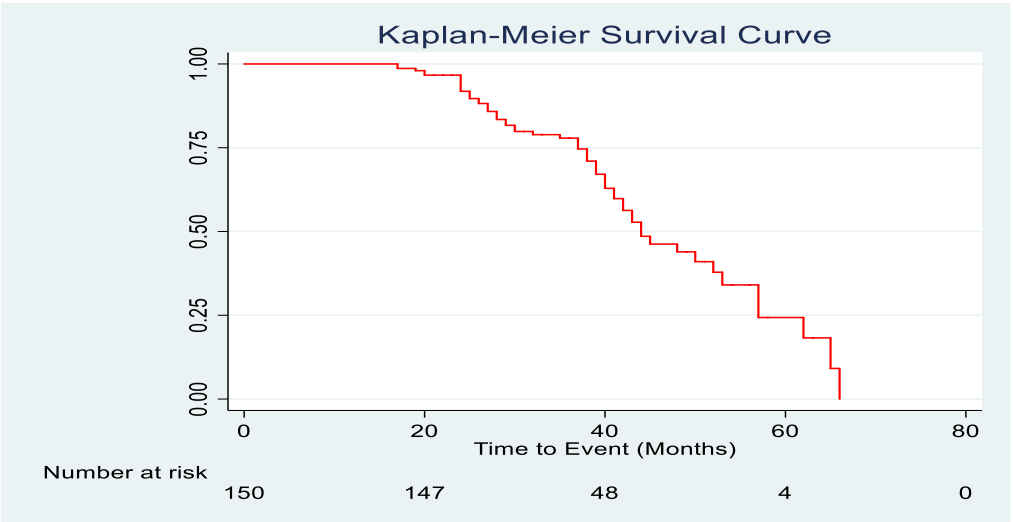

Figure 1: The Kaplan-Meier Survival Curve

The Kaplan–Meier survival estimate presented in Fig. 1 demonstrates a gradual but consistent decline in the survival probability of patients with chronic hepatitis B over time, most notably between 20 and 60 months. Survival decreases from nearly 100% to 0%, with the sharpest reduction occurring between 30 and 60 months. The smaller number of patients remaining at risk toward the end of the follow-up period indicates that most individuals had either experienced the event or were censored. Overall, the curve shows that long-term survival in this study is limited, highlighting the importance of early intervention, particularly within the first two to three years of follow-up.

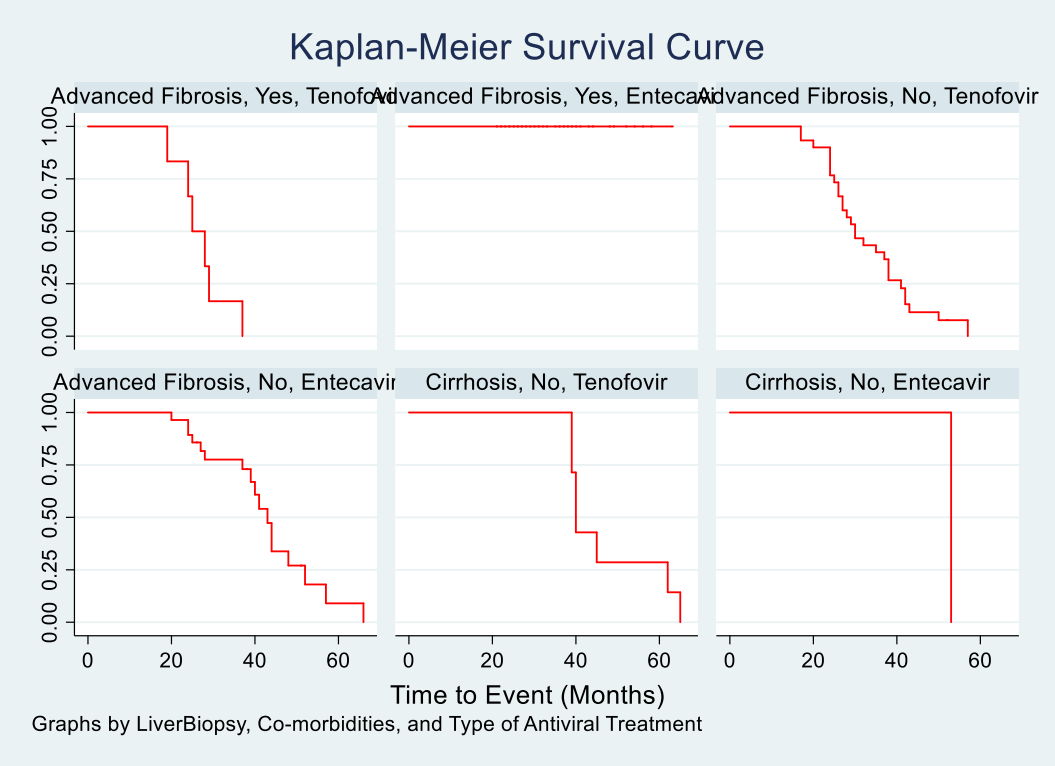

Figure 2: The Kaplan-Meier Hazard Curve

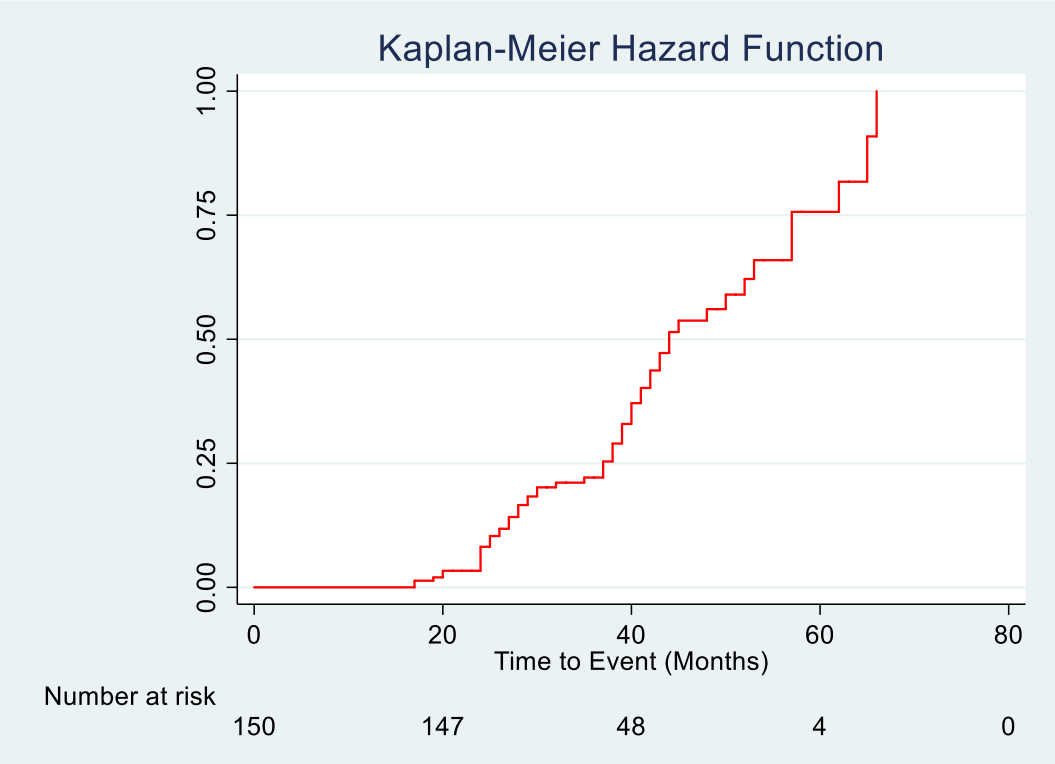

Figure 3: The Kaplan-Meier Survival Curve for Subgroups

Table 4 presents the results of model selection based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for the Cox Proportional Hazards Model (CPHM) and several Accelerated Failure Time (AFT) models. The results show that the Cox model had the highest AIC (409.73) and BIC (433.82), suggesting a poor fit to the data compared to the parametric alternatives. The exponential AFT model showed some improvement (AIC = 183.57; BIC = 210.67), but its fit was still weaker than the other parametric models. The Weibull AFT model produced a much better fit (AIC = 84.05; BIC = 114.15), indicating that allowing the hazard to vary over time captures the survival experience of patients more accurately. Further improvement was observed with the log-logistic AFT model (AIC = 74.33; BIC = 104.43). However, the log-normal AFT model had the lowest AIC (71.52) and BIC (101.63), making it the best-fitting model among all those considered. Overall, both AIC and BIC consistently identified the log-normal AFT model as the most appropriate model for the survival analysis of chronic Hepatitis B patients at Federal Medical Centre, Nguru. The log-normal model provides the best statistical fit and was therefore selected for further interpretation. The lognormal accelerated failure time (AFT) model revealed that several clinical and demographic factors significantly influenced the survival of chronic hepatitis B patients at FMC Nguru. Male gender was associated with shorter survival (TR = 0.887, p = 0.013), which aligns with previous findings suggesting that men often experience more aggressive progression of HBV-related liver disease compared to women (Yang et al., 2019). Age at diagnosis also negatively impacted survival, with each additional year reducing survival time by about 0.8% (TR = 0.992, p = 0.005). This finding is consistent with prior studies reporting that older patients present with more advanced disease and poorer prognosis (Chen et al., 2016). The severity of liver disease was one of the strongest predictors of mortality. Patients with advanced METAVIR fibrosis or cirrhosis survived only 23.5% as long as those with less severe disease (TR = 0.235, p < 0.001). This corroborates earlier evidence that fibrosis stage is a critical determinant of survival in chronic HBV infection (Liaw & Chu, 2009; Papatheodoridis et al., 2015). Elevated liver enzymes (AST and ALT) were also significant predictors, were 1-unit increase in AST and ALT reduced survival time by 0.3% and 0.4% respectively, reflecting active liver inflammation and ongoing hepatocellular damage, findings consistent with those of Musa et al. (2015). Comorbidities such as HIV, diabetes, or hypertension reduced survival time to 26.2% compared with patients without additional conditions (TR = 0.262, p < 0.001). Similar results have been reported by Matthews et al. (2014), who emphasized the adverse impact of co-infections and metabolic disorders on HBV prognosis. In contrast, antiviral therapy demonstrated a profound protective effect. Patients on treatment had survival times approximately four times longer than untreated patients (TR = 4.014, p < 0.001). This finding is strongly supported by previous studies, which have consistently shown that antiviral therapy, particularly Tenofovir and Entecavir, reduces the risk of cirrhosis, hepatocellular carcinoma, and HBV-related mortality (Lok et al., 2016; Revill et al., 2023). The model was statistically significant overall (likelihood ratio χ^2 = 87.64, p < 0.001), indicating that the covariates collectively explained substantial variation in patient survival. Taken together, these findings confirm the importance of early diagnosis, fibrosis staging, and timely initiation of antiviral therapy, in agreement with established evidence across sub-Saharan Africa.

CONCLUSION

This study compared non-parametric, semi-parametric, and parametric survival models to evaluate prognostic factors among chronic hepatitis B patients at Federal Medical Centre, Nguru. The Kaplan–Meier analysis revealed limited long-term survival, particularly within the first 30 to 60 months after diagnosis. Model selection based on AIC and BIC identified the lognormal AFT model as the best-fitting approach, outperforming the Cox proportional hazards and other parametric models. The lognormal AFT model highlighted age at diagnosis, fibrosis stage, liver enzyme levels, and comorbidities as significant predictors of reduced survival, while antiviral therapy markedly prolonged survival. These findings emphasize the importance of early screening, timely staging of liver disease, and initiation of antiviral treatment to improve patient outcomes. From a policy perspective, strengthening access to affordable diagnostics and expanding treatment coverage could reduce hepatitis B–related mortality in Northern Nigeria. Despite the valuable insights provided, this study is constrained by its relatively small sample size and single-centre data, which may limit the generalizability of the findings to broader populations. Future studies with larger and multi-centre cohorts are recommended to validate the model performance and enhance the robustness of the conclusions.

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