SPCBIC 2024

22nd – 24th April,

Minna Nigeria

4th SCHOOL OF PHYSICAL SCIENCES BIENNIAL INTERNATIONAL CONFERENCE (SPSBIC 2024)

Conference Proceedings

THEME:

Innovative scientific research: A tool for socioeconomic development and environmental sustainability

Federal University of Technology Minna,
Niger State, Nigeria

THEME OF THE CONFERENCE

Innovative scientific research: A tool for socioeconomic development and environmental sustainability.

SUB-THEMES OF THE CONFERENCE

- Advancement in Materials Science and Technology for Sustainable Development
- Modeling, Theory and Applications
- Climate Sustainability and Sustainable Development Goals
- Science, Technology and Innovation, and the Journey to a Net Zero Energy Future for Africa

PRE-CONFERENCE WORKSHOP TITLE

Publication in Impact Factor Journal: Challenge and Breakthrough

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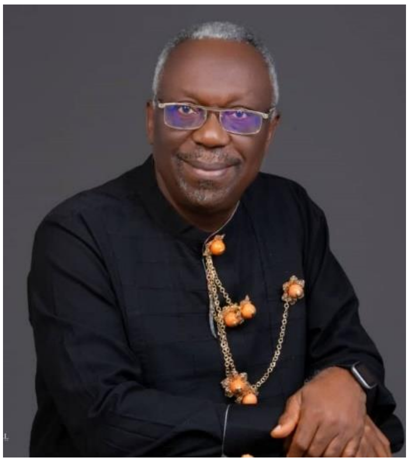

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Topic: ***Science, Technology, and Innovation and the Journey to a Net Zero Energy Future for Africa***

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CONFERENCE WORKSHOP FACILITATOR

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Department of Physics, Federal university of Technology, Minna, Niger State
Topic: ***Publication in Impact Factor Journal: Challenge and Breakthrough***

Chairman's Remark

It is with great pleasure and a deep sense of responsibility that I welcome you all to this important conference, themed "Innovative scientific research: A tool for socioeconomic development and environmental sustainability." As Chairman of the Conference Planning Committee, I am truly honored to share a few remarks at this pivotal moment.

This gathering was not just a meeting of minds; it was a convergence of visionaries, scholars, industry experts, policymakers, and young professionals committed to shaping a better future through collaboration, research, and practical innovation. Our theme reflects the urgency of our times—recognizing that sustainable progress hinges on our willingness to challenge the status quo, embrace change, and work across disciplines.

The planning and execution of this conference has been a journey of diligence and commitment. I would like to acknowledge the unwavering efforts of the organizing committee members, the Dean of our great school; Professor Jiya Mohammed, academic members of the school, and every stakeholder who contributed in various ways to make this event a reality. Special thanks go to our amiable Vice Chancellor and his management team, keynote speakers, presenters, and panelists who had travelled far and near to share their insights and experiences with us.

Over the course of this conference, we had explored a variety of sub-themes ranging from renewable energy and environmental sustainability, to technological innovations, policy frameworks, and inclusive economic growth. We believe that the sessions, workshops, and discussions lined up did not only spark intellectual curiosity but also inspire actionable solutions for local and global challenges.

It is also our hope that beyond the formal sessions, meaningful connections and collaborations would have been formed. Conferences like this serve as fertile ground for networking, mentorship, and the cross-pollination of ideas—elements that are crucial for long-term impact.

In conclusion, I encourage all participants who actively engaged in the conference, to have this carefully packaged pieces of academic presentations in the form of conference proceeding as a document for intellectual use. Let this conference be remembered not just for the ideas exchanged, but for the seeds of change it sows in our respective fields.

Thank you for your attention, and once again, welcome.

Professor Usman Shehu ONODUKU, PhD
Chairman, Conference Planning Committee
April 21-25th, 2024

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2024SPSBIC0090

Modelling of Diabetic Patients' Treatment Compliance and Their Survival Patterns in Nigeria: A Survival Analysis Approach

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Abstract

This study investigates the Diabetic Patients' Treatment Compliance and their Survival Patterns in Nigeria using secondary data from the University of Ilorin Teaching Hospital, Ilorin, Kwara State, Nigeria, spanning the years 2020 to 2023. Employing a comprehensive analysis, the study assessed parametric, semi-parametric, and nonparametric approaches, with time to recovery from diabetes infection as the primary outcome variable. Four covariates including gender, age, years of admission, and categories of diabetes were considered in the analysis. Model selection criteria relied on the Akaike and Bayesian Information Criteria (AIC and BIC). Results indicate that age, years of admission and categories of diabetes significantly contribute to the patients' treatment compliance and their survival patterns, as evidenced by the estimated survival rates. Additionally, the log-rank test was employed to compare survival curves across different values of the variables. Significant statistical differences were observed at a 0.05 level of significance among various age groups, years of admission and categories of diabetes. The study further underscores the significant influence of age, years of admission and categories of diabetes on patients' survival patterns, with age, years of admission and categories of diabetes revealed a significant role in all models (Cox, exponential and Weibul models). Notably, parametric models consistently identified age, years of admission and categories of diabetes as significant covariates, while the Cox model highlighted age and years of admission as the significant covariates. Based on the findings, early hospital intervention and treatment compliance are recommended for diabetic patients to ensure optimal care, particularly considering the critical role of the categories of diabetes. Moreover, the study recommends the Exponential model as the most suitable fit for diabetes data, irrespective of sample size, and emphasizes the parametric models' approach as the preferred strategy for analyzing diabetes data.

KEYWORDS: *Survival Analysis, Diabetes, Cox proportional Regression, Kaplan-Meire Estimator, Nigeria.*

1.0 Introduction

In a few years, diabetes mellitus (DM), a rising public health concern of the twenty-first century, could bankrupt the healthcare sector (Owolabi *et al.*, 2020). Regretfully, almost all of diabetics in developing nations are between the ages of 45 and 64, when most individuals are supposed to be productive and the key to achieving the socioeconomic goals of their country (Kambinda, 2017). Diabetes not only lowers productivity but also has a significant financial cost due to missed economic development, increased healthcare costs, and loss of production (Afroz *et al*., 2020).

DM is a dangerous illness for both an individual and the community (Oruh *et al.*, 2021). Among numerous groups, the illness is most prevalent among people over 70 years of age. Yet, rates of incidence are increasing dramatically among people in the emerging nations who are of working age (Oruh *et al*., 2021). The rising incidence of the disease is concerning and is linked to several variables such as aging populations, poor dietary habits, obesity, and inactivity. High blood glucose levels, which are caused by abnormalities in insulin secretion, action, or both, are frequently the outcome of the disease. Diabetes comes in three varieties. According to Kumar *et al.* (2020), these include types 1 and 2 diabetes and gestational diabetes. Type 2 diabetes results from being resistant to the effects of insulin, whereas type 1 diabetes is caused by a decrease in insulin production. Nevertheless, hyperglycemia results from both kinds (Wolosowicz *et al*., 2020).

The rising percentage of persons with type-2 diabetes, which makes up 90% of all instances of the disease, is a global issue and has emerged as a leading cause of early illness and death (Zheng *et al*., 2018). Type-2 diabetes seems to be fueled by fast cultural shifts, elderly people, changes in diets, less exercise, and other poor lifestyle choices in developing nations, particularly in sub-Saharan Africa (Misra *et al*., 2019). These factors are all linked to the acceptance of western values and urbanization. The World Health Organization (W.H.O) reported in 2023 that 11 million Nigerians were living with coping with diabetes, and this number is expected to rise to 1.3 billion by the year 2050 (Culberson *et al*., 2023).

One persistent disease where autonomy is essential to treatment is diabetes (Silva *et al.*, 2018). According to Arrieta Valero (2019), autonomy is a natural progression of understanding or consciousness improvement through acquiring knowledge to deal with the complicated nature of diabetes in a social setting. Patients and their relatives oversee the great bulk of daily care for those with diabetes. People with diabetes who practice these seven crucial self-care behaviors are more likely to have positive outcomes. These include maintaining a nutritious diet, getting regular exercise, checking blood sugar, taking medications as prescribed, using sound coping mechanisms, and reducing risk. People with or at risk for diabetes engage in self-care behaviors to effectively manage the condition on their own (ADCES7 & Kolb, 2021). These treatment or care methods need to be continued for the rest of one's life unless diabetes can be cured (American Diabetes Association, 2019).

Research from all around sub-Saharan Africa points to a low diagnosis rate for diabetes. For instance, 60% of diabetes cases in research conducted in Cameroon (Nansseu *et al.*, 2019) were undetected. According to Asamoah-Boaheng *et al.* (2019), the comparable percentage was 70% in Ghana and more than 80% in Tanzania (Osetinsky *et al*., 2022). According to reports, both the diagnosis and the standard of treatment for diabetes patients in sub-Saharan Africa are poor (Pastakia *et al*., 2017). Lack of clinics accessibility and medication availability, excessive healthcare and treatment expenses, a shortage of qualified personnel and equipment, and the use of alternative health care practitioners like herbalists and/or traditional healers are the noted causes of these trends (Mekashaw Bayked *et al*., 2022). Some folks find that trado medication works well as well. Poor diabetes treatment and care results have also been linked to inadequate knowledge among patients on diabetes management, which includes self-monitoring and maintenance of glycaemic levels, failure to adhere to medication regimens, and ineffective medical beliefs or perceptions about the management of this disease (Fabrizi *et al.,* 2020). Basic data on them is required in order to create a biopsychosocial and educational program aimed at helping individuals living with diabetes. These comprise the knowledge, attitudes, and opinions that patients have about the condition, as well as compliance-related elements and the experiences that patients have connected to their sickness. The purpose of this research is to investigate these categories of behavioral antecedents' factors.

It has been claimed that there are currently about 11 million diabetics in Nigeria (Uloko *et al*., 2018). This suggests that the illness is quietly and broadly expanding throughout the nation. Over 80% of the increase in diabetes patients worldwide is predicted to occur in emerging countries by 2030. The expense is just not comparable in Nigeria. People with diabetes will be impacted the most from this explosive expansion, and healthcare providers will inevitably falter financially as a result. 536.6 million Individuals globally suffer with Type 2 diabetes at the moment. Over 555 million people would be impacted by 2030; developing nations like Nigeria are predicted to account for 70 percent of this growth which is worrisome. Of those impacted, 50% do not yet have a diagnosis. According to the Lai *et al*. (2017), one person dies from diabetes every ten seconds and two people acquire the disease every ten seconds.

Furthermore, it is an issue that needs to be addressed when diabetes individuals visit hospitals on a regular basis, yet their blood glucose levels don't go down even after receiving medication. One of the biggest obstacles to the management of diabetes in Nigeria is the non-adherence of diabetic patients to prescribed medications and diets. Patients with diabetes must avoid certain behaviors that can raise their blood sugar levels and cause problems, some of which may even be fatal.

There are several factors contributing to the poor glycemic control among diabetic patients in Nigeria. Financial constraints play a major role because the majority of patients must pay for their medications and blood glucose testing themselves, and these costs have been found to be significantly higher than those of similar medications in other countries (The diabetes declaration and plan for Africa 2006). In Nigeria, patients bear a significant share of the medical expenses (74.5%), with the government covering only 25.5% of medical costs (Ozoh *et al.*, 2021). According to the WHO data, 90.2% of Nigerians make less than $2 per day. For this reason, getting health treatment in Nigeria might be difficult for those who have diabetes (Oyelami *et al*., 2019).

Similarly, it is difficult to follow medical advice while dealing with an illness like diabetes. As the study found, an individual's capacity to adhere to treatment can be negatively impacted by a number of factors, including the intricacy of certain pharmaceutical treatments, the challenge of following a diet, anxiety related to receiving insulin injections, fear of hypoglycemia, and gaining weight. Research has shown that in order to reduce major long-term problems, it is crucial to achieve optimal glucose management with rigorous adherence to diets and drugs (Awuchi *et al.*, 2020). Developing educational and health promotion initiatives with the goal of helping diabetic patients achieve better glycemic control is crucial. It is imperative to acknowledge the experiences of individuals with diabetes and the behavioral aspects that impact their adherence to suggested health measures. Consequently, the results of this research will serve as baseline data for the development of social support networks, patient education programs, and successful self-care measures for diabetic patients, particularly in healthcare settings.

2.0 Materials and Methods

2.1 Data Description

Six hundred and four (604) registered diabetic patients with medical histories at the University of Ilorin Teaching Hospital provided the secondary data. For a four-year period, from 2020 to 2023, data is gathered based on the length of hospital stay, sex, age, and classifications of diabetes, respectively.

Table 1: **Data Presentation**

Covariates	Groups	Frequency	Events	N Censored	Valid percentage (%)	Cumulative percentage (%)
Gender	Male	294	105	189	48.7	48.7
	Female	310	105	205	51.3	100.0
	Total	**604**	**210**	**394**	**100**	
Age	0-14 years	42	2	40	7.0%	7.0
	15-29 years	81	13	68	13.4%	20.4
	30-44 years	249	24	225	41.2%	61.6
	45-59 years	91	71	20	15.1%	76.7
	60-84 years	111	98	13	18.4%	95.1
	85-94 years	30	2	28	4.9%	100
	Total	**604**	**210**	**394**	**100.0%**	
Years of Admission	2020	101	85	16	16.7	16.7
	2021	161	34	127	26.7	43.4
	2022	279	67	212	46.2	89.6
	2023	63	24	39	10.4	100.0
	Total	**604**	**210**	**394**	**100.0**	
Categories of Diabetes	Gestational	79	22	57	13.1	13.1
	Type 2	231	113	118	38.2	51.3
	Type 1	294	75	219	48.7	100.0
	Total	**604**	**210**	**394**	**100.0**	

Table 1 shows the summary of covariates considered in this study and it was observed that two hundred and ten (210) patients got the event (i.e dead) in each covariate out of the records of six hundred and four (604) patients' data collected.

2.2 Methodology

Censoring in survival analysis occurs when the exact survival time of a subject cannot be accurately determined. This means that some information about an individual's survival time is known but the actual survival time is not known exactly. There are three main reasons why censoring may occur which are: (i) when a person does not experience the event before the **study ends** (ii) when a person is **lost to follow-up** during the study period, and (iii) when a person **withdraws** from the study because of death (if death is not the event of interest) or some other reasons like adverse drug reaction, or other competing risks (Schober & Vetter, 2018).

Censoring is an important issue i.e a key analytical problem that cannot be escaped in survival analysis, therefore some statistical methods cannot be used to analyze survival data because they neglect censored data which must be independent of the survival mechanism (Chakraborty., 2018).

$$h(t) = h(t) = \lim_{\Delta t \to 0} \frac{Pr(t < T \leq t + \Delta t \mid T > t)}{\Delta t} = \frac{f(t)}{S(t)} \quad (1)$$

The hazard function, denoted by $h(t)$, is given by the formula: $h(t)$ equals the limit, as Δt approaches zero of a probability statement about survival, divided by Δt, where Δt denotes a small interval of time. This mathematical formula is difficult to explain in practical terms. Where

h(t) = Hazard function

S(t) = Survivor function

T = Random variable for a person's Survival time

t = Specific value of T

Δt = change in the specific value of T

Kaplan-Meier Method

The Kaplan Meier method is the most widely used method in survival data analysis and is also known as *Product Limit Estimate*. This method provides very useful estimates of survival probabilities and graphical presentation of survival distribution. This method assumes that the censoring times are independent of the survival times, i.e the reason an observation is censored is unrelated to the cause of death, but this assumption is only true if the patient is still alive at the end of the study period.

$$\hat{S}(t) = \prod j{:}\, tj \leq t \, \frac{(r_j - d_j)}{r_j} \quad , for\ 0 \leq t \leq t \quad (2)$$

In the above equation i,j = 1,2,…n is the total set of failure times recorded (with t the maximum failure time), dj is the number of failures at time tj, and rj is the number of individuals at risk at time tj.

Log Rank Test

The Log-rank test is a large sample chi-square test that uses as its test criterion a statistic that provides an overall comparison of the KM curves being compared. It is applicable to data where there is progressive censoring and gives equal weight to early and late failures. These statistics, like many others, uses the observed and expected cell counts over categories of outcomes where the categories for the log-rank statistic are defined by each of the ordered failure times for the entire set of data being analyzed. It is also a test used for comparing survival distributions for two or more groups and assumes that hazard functions for the two groups are parallel. When two groups are being compared, a statistic with 1 degree of freedom (known as log-rank test statistic) is formed using the sum of the observed minus expected counts overall failure times for one of the two groups. The test statistic can be expressed as;

$\frac{(Oi-Ei)^2}{Var(Oi-Ei)}, i = 1,2. \quad x^2\ 1, df$ (3)

$O_i - E_i$ = summed observed score minus expected score

Var $(O_i - E_i)$ = variance of summed observed score minus expected score

$O_i - E_i = \sum_j (mi\ j\ -\ ei\ j\ )$ and

$Var(Oi - Ei) = \sum_j \frac{n1\ jn2\ j\ (m1\ j + m2\ j\ )(n1\ j + n2\ j - m1\ j - m2\ j\ )}{(n1j+n2j)2(n1j+n2j-1)}$, i = 1, 2 (4)

Cox Proportional Hazards model

An important property of the Cox model is that the baseline hazard, (t), is an unspecified function. It is this property that makes the Cox model a **semi-parametric** model and a popular one. A key reason for the popularity of the Cox model is that, even though the baseline hazard is not specified, reasonably good estimates of regression coefficients, hazard ratios of interest, and adjusted survival curves can be obtained for a wide variety of data situations. Also, the Cox PH model is a “robust” model (i.e., it will closely approximate the correct parametric model), so that the results from using the Cox model will closely approximate the results for the correct parametric model. Another attractive feature of the Cox model is that it is still feasible to predict the β's in the exponential portion of the model despite not specifying the model's baseline risk portion. The hazard ratio, which is an impact metric, is calculated without the baseline hazard function needing to be bothered. Also, another important property of the Cox model is that the baseline hazard, $h_o(t)$, is an unspecified function. It is this property that makes the Cox model a **semi-parametric** model.

The general form of the Cox model is given by;

$h(t, x) = h_o(t)\ exp \sum_{i=1}^{p} \beta i\ Xi$, i.e h_o(t)$e^{(\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots)}$ (5)

Where $h_o(t)$ is the baseline hazard and the β_i's are the regression coefficient with i = 1,2,3, … , p and X's are the explanatory variables.

The equation parameters are estimated using partial probability. This method requires censored information into account. The matrix of probability is the result of the number of moments of failure say k,

$L = \prod_{j=1}^{k} L_{j=}$ (β)= $\prod \frac{expXi\beta i}{\sum_{Y j \geq Y i} expXj\beta}$, (6)

Where k is the number of observations for which we have observed an event (where generally there were n observations, so k-n observations were censored).

Acceleration Failure Time (AFT): With this kind of parametric model, the length of survival is expressed as a function of variables, and a change in one explanatory parameter corresponds to a change in the time to death. The advantage of the AFT method is that the impact of variables on survival may be described in absolute terms, like years, instead of using comparative terms like a hazard ratio.

An AFT model is a parametric model that provides an alternative to the frequently employed proportional hazards models (Burke *et al*., 2020).

Exponential Model:

The exponential model, which is a one-parameter distribution with a constant risk rate (λ) as time passes (h(t)=λ), is the most fundamental and important model in survival study. A high λ value indicates a high probability of a shorter survival, whereas a low number indicates a lengthy survival. It's widely recognized for its pronounced "lack of memory" and is also called a completely randomized failure trend. It has been used in numerous studies to explain a variety of issues, including ledger issues, bank records, inaccurate salary checks, and the life cycles of digital systems (Amran, 2018). It is given mathematically as.

$h(t) = h_0\ exp^{\beta x} \quad where\ h_0 = \lambda$ (7)

Weibul Model:

The Weibull distribution is a generalization of the exponential distribution. However, unlike the exponential distribution, it does not assume a constant hazard rate and therefore has broader application. The distribution was proposed by Weibull in 1939 and its applicability to various failure situations was discussed again by Weibull in 1951. It has then been used in many studies of reliability and human disease mortality. The Weibull distribution is characterized by two parameters, γ and λ. The value of γ determines the shape of the distribution curve and the value of λ determines its scaling. Consequently, γ and λ are called the *shape* and *scale parameters*, respectively. When γ =1, the hazard rate remains constant as time increases; this is the exponential case. The hazard rate increases when γ >1 and decreases when γ <1 as *t* increases. Thus, the Weibull distribution may be used to model the survival distribution of a population with increasing, decreasing, or constant risk. Examples of increasing and decreasing hazard rates are, respectively, patients with lung cancer and patients who undergo successful major surgery, (Elisa and John, 2003). The probability density function, cumulative distribution function, hazard function and the survival function are given respectively,

$f(t) = \lambda\,\gamma(\lambda t)^{\gamma-1}\, e^{-(\lambda t)^{\gamma}}$, t≥0, λ and γ >0

$F(t) = 1 - e^{-(\lambda t)^{\gamma}}$

$h(t) = \lambda\,\gamma(\lambda t)^{\gamma-1}$

$S(t) = e^{-(\lambda t)^{\gamma}}$

3.0 Analysis

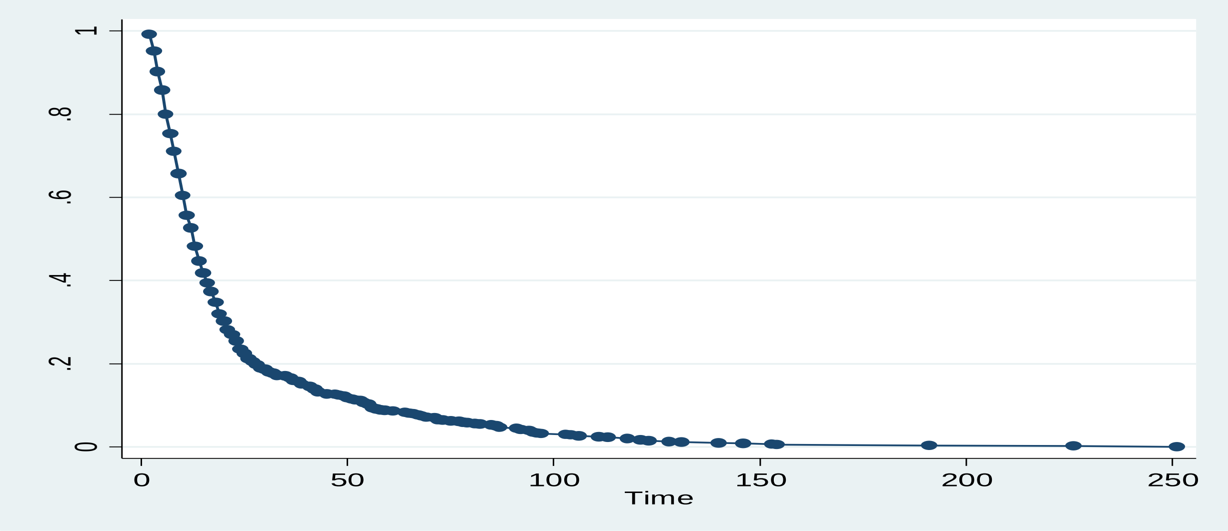

Figure 1: Summary of events history of diabetic patients

Figure 1 reveals the survivorship function based on the total number of patients under study with the number at risk at different time points.

3.1 Kaplan-Meier Survival Curves

The figure below shows the general Kaplan-Meier survival curves for all contributing covariates for the diabetic patients.

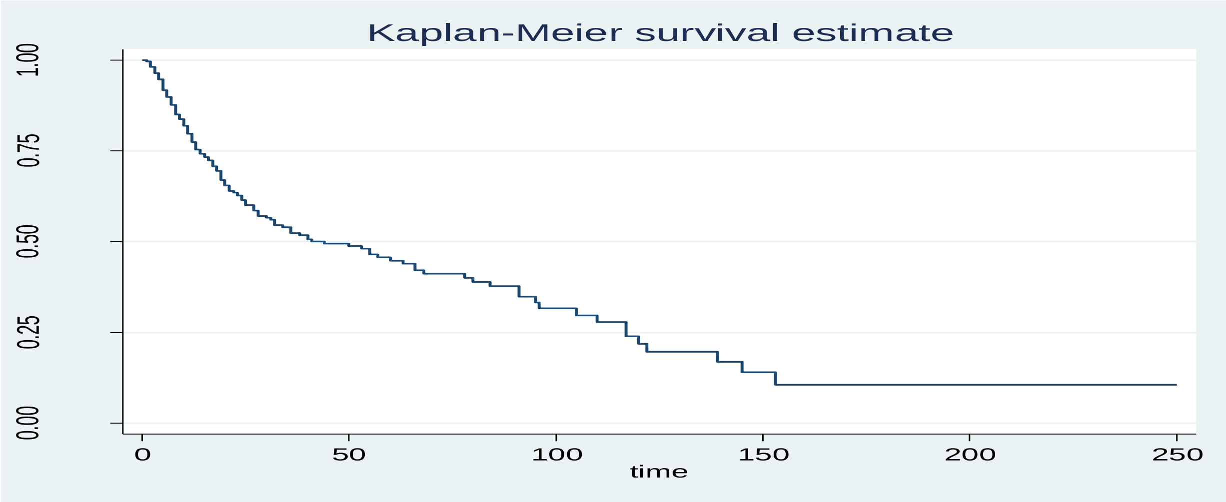

Figure 2: General survival curve for all diabetic patients under study

Figure 2 shows the survivorship function based on the total number of patients under study with the number at risk at different time points.

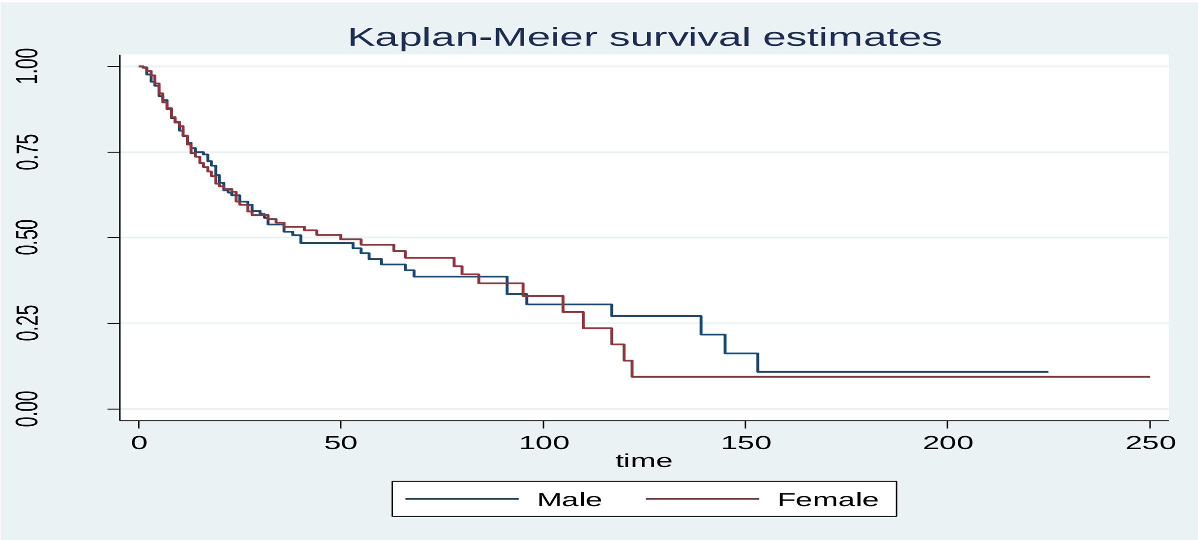

Figure 3: Survival curve based on the gender of diabetic patients.

Figure 3 reveals the survivorship function based on the gender of diabetic patients with the number at risk at different time points.

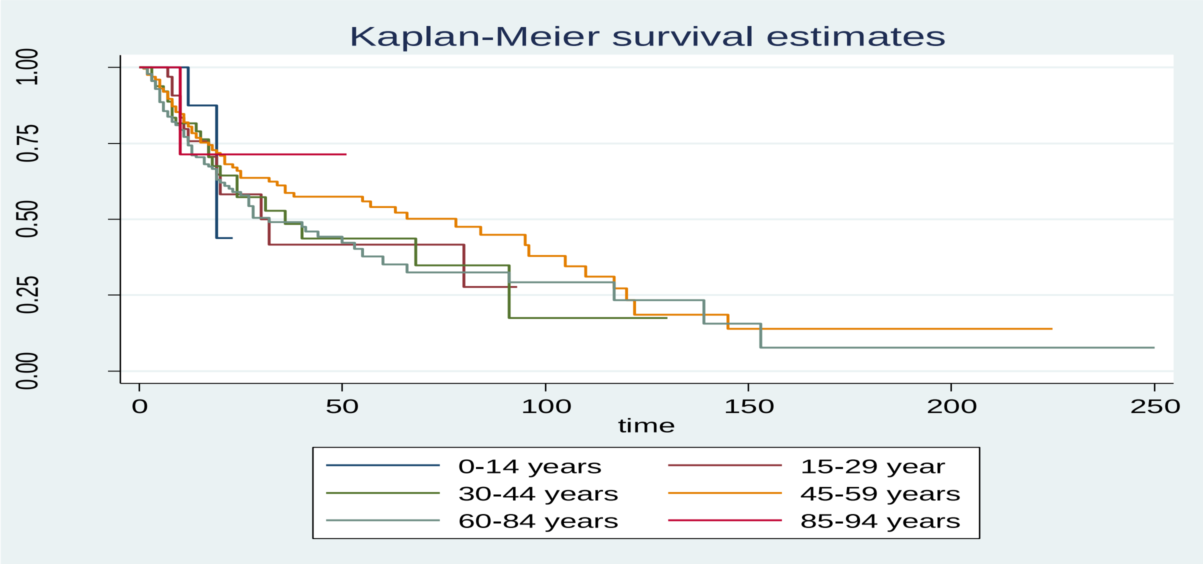

Figure 4: Survival curve based on the age range of diabetic patients.

Figure 4 indicates the survivorship function based on the patients' age distributions with the number at risk at different time points.

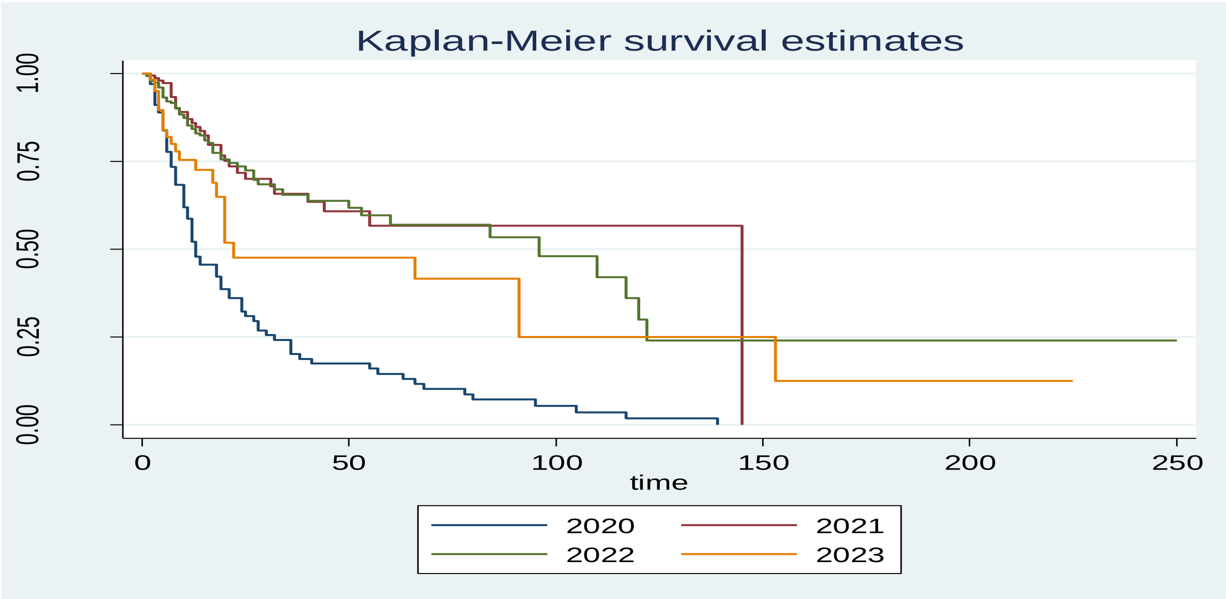

Figure 5: Survival curve based on the years of admission of diabetic patients.

Figure 5 shows the survivorship function based on the patients' years of admission with the number at risk at different time points.

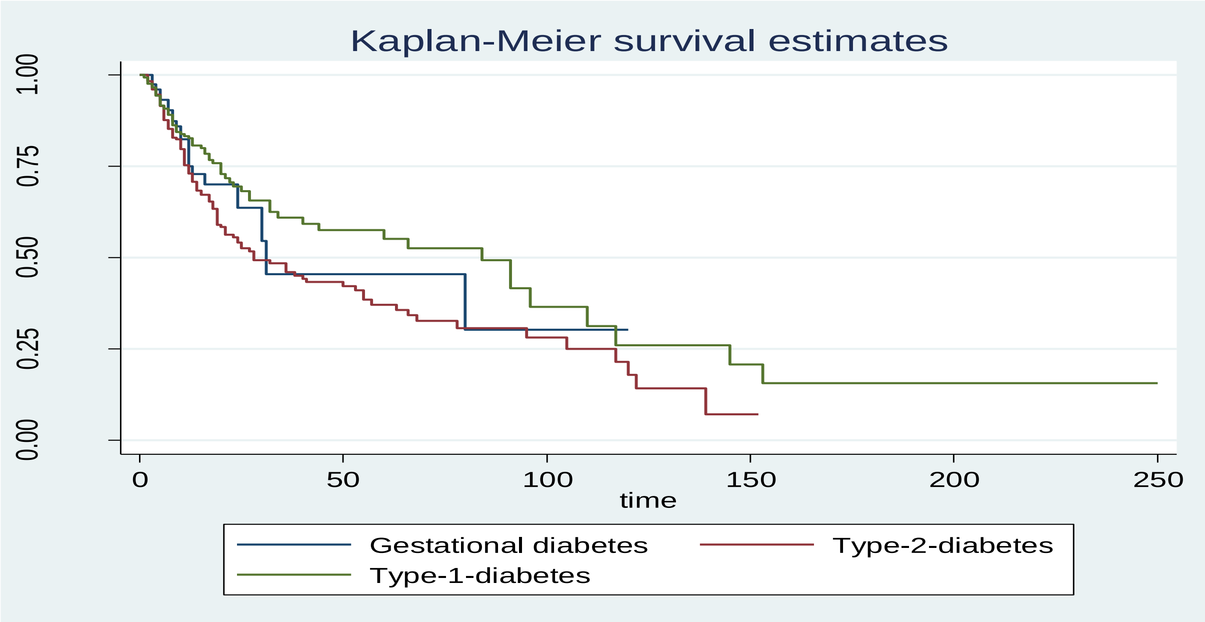

Figure 6: Survival curve based on types of diabetes diagnosed for the patients.

Figure 6 reveals the survivorship function based on types of diabetes diagnosed for the patients with the number at risk at different time points.

3.2 Log-Rank Test for Equality of Survivor Functions

3.2.1 Log-rank Statistic

$\sum \frac{(O_i - E_i)^2}{Var(O_i - E_i)}$, i = 1, 2, 3… ~ $\chi^2_{(df)}$ i = 1, 2, 3…

H_o: Survival curves for covariates are the same.

vs

H_1: Survival curves for covariates are not the same.

Decision rule: Reject H_o if p-value < α-level (0.05). Otherwise, do not reject H_o.

Table 2: Log-rank Test forDifferent Risk Factors Associated with Diabetic Patients in Nigeria

Covariates	Groups	Events Observed	Events Expected	Chi-Square (χ^2)	p-value
Gender	Male	105	106.11	0.02	0.8764
	Female	105	103.89		
	Total	**210**	**210**		
Age	0-14 years	2	3.2	5.04	**0.0104**
	15-29 years	13	12.7		
	30-44 years	24	22.96		
	45-59 years	71	83.65		
	60-84 years	98	84.5		
	85-94 years	2	2.99		
	Total	**210**	**210**		
Years of Admission	2020	85	35.4	89.86	**0.0001**
	2021	34	55.03		

	2022	67	98.56		
	2023	24	21.01		
	Total	**210**	**210**		
	Gestational Diabetes	22	22.64		
Categories of Diabetes	Type-2-Diabetes	113	93.44	8.21	**0.0165**
	Type-1-Diabetes	75	93.92		
	Total	**210**	**210**		

Decision: Since the p-values= 0.0104, 0.0001 and 0.0165 < α=0.05. The null hypothesis (H_o) is therefore rejected for the patients' age, their years of admission as well as the types of diabetes they were diagnosed for.

Conclusion: Since the null hypotheses have been rejected in favor of the alternative hypotheses for the patients' age, their years of admission as well as the types of diabetes they were diagnosed for. It can therefore be concluded that patients' age, their years of admission as well as the types of diabetes they were diagnosed for have significant different K-M survival curves. Thus, it implies that patients' age, their years of admission as well as the types of diabetes they were diagnosed for do affect their survival patterns.

3.3 Cox Proportional Model

No. of subjects = 604 Number of obs = 604

No. of failures = 210

Time at risk = 13360

LR chi2(12) = 78.78

Log likelihood = -1102.4353 Prob > chi2 = 0.0001

Table 3:	**Cox Proportional Hazard Results**						
Covariates	Coefficients (β)	Haz. Ratio	Std. Err.	z	P>z	[95% Conf.	
GENDER							
Female	-0.1044	0.9009	0.1287	-0.7300	0.4650	0.6808	1.1921
AGE							
15-29 years	0.4222	1.5253	1.1655	0.5500	0.0581	0.3411	6.8197
30-44 years	0.6109	1.8420	1.3614	0.8300	0.0480	0.4327	7.8414
45-59 years	0.3718	1.4504	1.0463	0.5200	0.0160	0.3527	5.9642
60-84 years	0.7268	2.0685	1.4864	1.0100	0.0120	0.5058	8.4593
85-94 years	-0.1342	0.8744	0.8770	-0.1300	0.0040	0.1225	6.2428
YEARS OF ADMISSION							
2021	-1.4553	0.2333	0.0507	-6.6900	0.0001	0.1524	0.3573
2022	-1.3549	0.2580	0.0542	-6.4400	0.0001	0.1708	0.3895
2023	-0.9603	0.3828	0.1220	-3.0100	0.0030	0.2049	0.7149
DIAGNOSIS							

Type-2-diabetes	-0.0877	0.9161	0.2353	-0.3400	0.3300	0.5538	1.5154
Type-1-diabetes	0.0241	1.0244	0.2983	0.0800	0.3400	0.5790	1.8126

The Estimated model: $\hat{h}(t, X) = h_o(t)e^{\beta X}$

$\hat{h}(t, X) = h_o(t)e^{\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k}$

Therefore, the cox model is given as:

$$\hat{h}(t, X) = h_o(t)\, e^{\substack{-0.1044_{female} + 0.4222_{15-29\ years} + 0.6109_{30-44\ years} + 0.3718_{45-59\ years} + 0.7268_{60-84\ years} - 0.1342_{85-94\ years} \\ -1.4553_{2021} - 1.3549_{2022} - 0.9603_{2023} - 0.0877_{type-2-diabetes} + 0.0241_{type-1-diabetes}}}$$

The Cox's Proportional Hazard Model was employed to determine the hazard ratio of the groups of covariates. The result obtained by the PHreg procedure is shown in Table 3 above.

The estimated regression coefficients, (coef), and the hazard ratio (exp (coef)) between the groups of covariates were obtained. Therefore, the hazard ratio which we will be used to interpret the cox proportional hazards model is compared based on its closeness to 1.

Therefore, the hazard ratio for male relative to female is -0.1044. Since these ratios is less than 1, it implies that male patients have a shorter survival time than female patients and the risk of dying from diabetes by male patients is -0.1044 times that of female patients. It was observed that the risk of dying based on gender is not significant since the p-value (0.4650) is greater than 0.05.

Furthermore, the hazard ratio for different age range relative to age category 0-14 years are 0.4222, 0.6109, 0.3718, 0.7268 and -0.1342. Since these ratios are less than 1, it means that patients within the age range 0-14 years have a shorter survival time than those in the age brackets 15-29 years, 30-44 years, 45-59 years, 60-84 years, and 85-94 years respectively.

The hazard ratio for different years of admission for the patients receiving treatment relative to the reference hazard (year 2020) are -1.4553, -1.3549, and -0.9603 for years 2021, 2022, and 2023 respectively. This means that, patients admitted for treatment in these years (2021, 2022, and 2023) have a lower risk and survive longer than the baseline hazard (year 2020). However, it was observed that year contribute significantly to the model.

Similarly, the hazard ratio for different categories of Diabetes were obtained. This means that, patients diagnosed with Type 1 diabetes and Type 2 diabetes have a better survival pattern (i.e. will survive from diabetes) relative to the baseline hazard (Gestational diabetes). However, it was observed that types of diabetes which patients were diagnosed for contribute significantly to the model.

3.4 Exponential Model with Accelerated Failure Time (AFT)

No. of subjects = 604 Number of observations = 604

No. of failures = 210 LR χ^2 (4) = 38.97

Time at risk = 13360 Prob > chi2= 0.0001

Log likelihood = -531.90964

Table 4: **Exponential Model**

Covariates	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gender	0.1355	0.1406	0.96	0.335	-0.1400	0.4109
Age	-0.0913	0.0791	-1.15	0.024	-0.2464	0.0638

Years of Admission	0.4965	0.0891	5.57	0.001	0.3219	0.6711
Diagnosis	-0.0734	0.1323	-0.55	0.053	-0.3327	0.1859
_cons	3.3434	0.4538	7.37	0.001	2.4539	4.2329

The exponential model fitted to the data is as follows.

$h(t) = \lambda = exp^{(\beta_o+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p)}$

Thus, the model fitted to the significant covariates is given below:

$h(t) = \lambda = exp^{(3.3434-0.0913_{Age}-0.4965_{years\ of\ admission}-0.0734_{diagnosis})}$

The significant covariates under exponential model are Age, years of admission and the categories of diabetes diagnosed patients for.

3.5 Weibul Model with Accelerated Failure Time (AFT)

No. of subjects = 604 Number of observations = 604

No. of failures = 210 LR χ^2 (4) = 38.42

Time at risk = 13360 Prob > chi2= 0.0001

Log likelihood = -531.43018

Table 5: Weibul Model

Covariates	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gender	0.1427	0.1475	0.97	0.333	-0.1464	0.4319
Age	-0.0935	0.0824	-1.13	0.027	-0.2551	0.0681
Years of admission	0.5192	0.0965	5.38	0.001	0.3301	0.7083
Diagnosis	-0.0810	0.1382	-0.59	0.058	-0.3519	0.1898
_cons	3.3332	0.4740	7.03	0.001	2.4041	4.2622
/ln_p	-0.0479	0.0496	-0.97	0.334	-0.1451	0.0493
p	0.9533	0.0473			0.8649	1.0506
1/p	1.0490	0.0520			0.9519	1.1562

The weibul model fitted to the data is as follows.

$h(t) = \lambda p t^{p-1}, where\ p\ and\ \lambda\ are > 0$

$h(t) = \lambda = exp^{(\beta_o+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_p X_p)}$

Thus, the model fitted to the significant covariates is given below:

$h(t) = \lambda = exp^{(3.3332-0.0935_{Age}+0.5192_{years\ of\ admission}-0.0810_{diagnosis})}$

The significant covariates under weibul model are Age, years of admission and the categories of diabetes diagnosed patients for.

Table 6: Model Selection Using Both AIC and BIC

Models	Number of Parameters (p)	Loglikelihood	AIC	BIC
Cox	4	-1102.4353	2226.871	2275.31
Exponential	4	-551.3942	**1073.819**	**1095.837**
Weibul	5	-531.43018	1074.86	1101.282

The Akaike Information Criterion (AIC) value is utilized to select the best fitted model among the three models that were fitted to the diabetes data, namely the **Cox proportional hazard models, Exponential, and Weibul**. The selected model is the **Exponential model**, which has the lowest AIC and BIC values, respectively.

4.0 Discussion of Findings

This study aimed to model the survival rate of Nigerian diabetic patients who do not comply with their medication regimen and to compare semi-parametric and some parametric models fitted to the diabetes data.

The Kaplan-Meier survival estimates showed that the overall survival rate of diabetic patients was considerably influenced by age, years of admission, and type of diabetes. Furthermore, the survival curves of the different stages of the variables were compared using the log-rank test. It was found that there were substantial differences ($p < 0.05$) between the survival experiences of the various age groups, years of admission, and diabetes categories. Though, gender did not differ significantly at the 0.05 level of significance.

Additionally, the age of the patients, the year of their admission, and the type of diabetes each represented three significant factors in the exponential and Weibul models in the presence of acceleration failure time (AFT). Nevertheless, the age of the patients and the year of admission were the only two factors that the Cox proportional hazard model could find a meaningful contribution from. As a result, it was shown that the two parametric models consistently benefited from the patients' age, years of admission, and diabetes categories. Conversely, the semi-parametric model developed was significantly influenced only by the age and year of admission of the patients.

Furthermore, it was demonstrated that the exponential model with AFT having the lowest AIC and BIC values was the best model suited to the sixty-four (604) diabetic patients' data.

4.1 Conclusion

The following findings were drawn from the examination of the data that was gathered.

i. At the 0.05 level of significance, the age of the patients, their diabetes categories, and the length of time they had been admitted all had a significant impact on the survival rate of diabetic patients.
ii. There was no discernible difference in the survival of diabetic patients according to gender at 0.05.
iii. The age of the patients, their diabetes classifications, and the years of admission were the three important factors in both the exponential and the Weibul models in the presence of AFT.
iv. The patients' ages, diabetes classifications, and years of admission were the only covariates that consistently showed significance in the parametric models that were fitted.
v. Only patients' age, and their years of admission were the significant covariates contributed to the Cox model.

4.2 Recommendations

Considering the findings of this study, I thus suggest the following:

i. For Nigerian medical professionals: Every healthcare provider will adhere to the International Diabetes Federation's approved diabetes management recommendations if policies and procedures are provided and enforced for all medical personnel and institutions. To guarantee adherence to diabetic standards, the health ministry should take the initiative in regulating, observing, and tracking the actions of healthcare practitioners. Additionally, to customize diabetes care and services to meet each patient's unique socioeconomic and cultural needs, healthcare practitioners must be aware of the obstacles to diabetes management.
ii. Diabetes (DM) patients' year of admission is sacrosanct. For appropriate care, individuals with diabetes should therefore make every effort to visit a hospital as soon as feasible.
iii. The most effective approach to use when studying diabetes data is to use parametric models.

Regardless of sample size, the exponential model with AFT provides the greatest fit to the diabetes data.

4.3 Suggestions for Further Study

This study suggested that to compare the survival rates of diabetic patients in Nigeria, prospective investigators should try to use other various parametric models in lieu of Weibul and exponential models.

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