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Relation between Accelerated Failure Time Models for Analyzing Hemodialysis Patients and Patient-Related Factors

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Abstract: *The accelerated failure time (AFT) model is a parametric survival model that can replace Proportional Hazards (PH) models. The AFT model has a major advantage in that it does not require the PH assumption. Recently in Sudan the end-stage renal disease (ESRD) has become a major health problem, hence the aim of this study was to compare different parametric (AFT) models, such as (Weibull, Exponential, log logistic, and lognormal), in hemodialysis patients to determine the best model for evaluating the variables associated with patient survival.325 hemodialysis patients were treated at public hospitals in Khartoum State during the period from December 2005 to December 2010.The data in this study was used to forecast survival function in order to classify hemodialysis patients based on patient-related factors influencing end-stage renal disease (ESRD). The Weibull model, which is based on Cox-Snell Residuals and the Bayesian Information Criterion (BIC), is useful among others models. Furthermore, both Diabetes mellitus and hypertension, normal, dialysis frequency per week, and hospitals were found to have a significant impact on survival (P<0.05) in accelerated failure time models. The Weibull model was found to have the smallest BIC (711.09) values in multivariate analysis, so it was chosen as the best model for hemodialysis patients.*

Keywords: Parametric modes, Proportional Hazards models, Hemodialysis, Accelerated failure time models, Cox-Snell residuals

المستخلص
نموذج وقت الفشل المتسارع (AFT) هو نموذج بقاء معلمي يمكن أن يكون البديل لنماذج المخاطر النسبية.يتميز نموذج وقت الفشل المتسارع بميزة كبرى من حيث انه لايتطلب افترض نماذج المخاطر النسبية.حديثا في السودان أصبح مرض الكلى في مراحله الأخيرة (ESRD) مشكلة صحية رئيسية. الهدف من هذه الدراسة هو تطبيق نماذج معلمية مختلفة مثل (Weibull ،Exponential ،Logistic ،Lognormal) في غسيل الكلى لتحديد أفضل نموذج للمرضى الذين يقومون بتقييم المتغيرات التي تؤثر على بقاء المريض. شارك 325 مريضا غسيل الكلى في هذه الدراسة. تم علاج هؤلاء المرضى في المستشفيات العامة بولاية الخرطوم خلال الفترة من ديسمبر 2005 إلى ديسمبر 2015. تم استخدام البيانات للتنبؤ بوظيفة البقاء على قيد الحياة من أجل تصنيف مرضى غسيل الكلى على أساس العوامل المتعلقة بالمريض والتي تؤثر على مرض الكلى في نهاية المرحلة (الداء الكلوي بمراحله الأخيرة). يعد نموذج Weibull ، الذي يعتمد على Cox-Snell Residuals ومعيار المعلومات Bayesian (BIC) ، مفيدًا من بين النماذج الأخرى. علاوة على ذلك ، وجد أن كلا من داء السكري وارتفاع ضغط الدم ، وتكرار غسيل الكلى أسبوعيًا ، والمستشفيات لهما تأثير كبير على البقاء على قيد الحياة (P <0.05) في نماذج وقت الفشل المتسارع. تم العثور على نموذج Weibull يحتوي على أصغر قيمBIC (711.09)فيالتحليل متعدد المتغيرات ، لذلك تم اختياره كأفضل نموذج لمرضى غسيل الكلى. يجب إجراء المزيد من الأبحاث حول الأسباب الجذرية للفشل الكلوي في السودان باستخدام نموذج كوكس للمخاطر النسبية ونماذج وقت الفشل المتسارع.

الكلمات المفتاحية:
النماذج المعلمية,نماذج المخاطر النسبية,الغسيل الدموي, نماذج الفشل المتسارع ,أخطاء كوكس سنيل

1. Introduction

Parametric models are always used for the analysis of survival data to assess the risk of death or chance of survival in a chronic hemodialysis patient. For physicians, making scores is really helpful, and the predictive method of choice for making such scores will be vital to producing accurate outcomes. In other words, the use of a mathematical model strengthens these approaches by allowing for simultaneous measurement of survival in relation to many factors and, moreover, produces estimates of the intensity of effect for each constituent element. The accelerated failure time (AFT) model is a parametric survival model that can replace Proportional Hazards (PH) models. A major advantage of the AFT model is that it does not require a PH assumption, and it may be easier to interpret the results. It is intended to evaluate the effects of covariates on the survival time of "speed up" or "reduce speed" One such model is AFT[1, 2, 3, 4, 5] and Exponential, Weibull, Log Logistic, Lognormal and Generalized Gamma AFT are the most commonly used models. The exponential and the Weibull parametric models can work in both PH and AFT metrics. Only the AFT metrics are used for logistic, lognormal, and generalized gamma models. The Gompertz model is a parametric relative hazard model, but is not an AFT model. The Accelerated Failure Time model works better than the Proportional Hazard Model in systems where treatment outcomes are expected to accelerate or prolong the occurrence of interest, although the Proportional Hazards are prevalent in the survival data study [**1,2, 4, 6]**.

In the last decade, Sudan has seen the expansion of its renal facilities both in the capital and in provincial hospitals. However, the shortage of needs remains strong and the demand for transplantation facilities is even higher due to the effects of the international embargo, as well as the epidemiological transformation marked by a resilient burden of infectious diseases, which has resulted in chronic diseases such as chronic renal failure. ESRD is one of the world's most important causes of morbidity and death observed last year. There is a drastic rise in renal failure among Sudanese citizens in Khartoum. Sudan's frequency-reported rate of new cases (ESRD) is 70-140 per million inhabitants/year**[7,8]**

The research focuses on one of the most common health conditions in both developed and developing countries, particularly End Stage Renal Disease (ESRD), a term used when the kidney approaches a total or nearly complete inability to function; kidneys can no longer expel waste, regulate and concentrate urine **[9].** Dialysis therapy is a treatment intended to remove excrement and toxic compounds in the body to compensate for the lack of kidney function. One class of dialysis is hemodialysis **[10]**.It has been estimated that over 1.1 million patients are estimated to have ESRD globally, with an addition of percent each year. Incidence and prevalence rates in the United States, for example, are expected to grow by 44 percent and 85 percent, respectively, from 2000 to 2015, and incidence and prevalence rates by 32 percent and 70 percent per million people. There are comparable patterns in the progress of ESRD patients in developed countries **[7, 11].** Scientific studies have uncovered major causes of end stage renal disease in survival time. These causes are affecting in the survival of hemodialysis patients for a live long time. The purpose of this research is to compare the performance of various parametric Accelerated Failure Time Models for Hemodialysis Patients. AFT models and their applications were used in order to estimate the survival probabilities which helps to identify the prognostic factors and to assess the effectiveness of the survival model that has resulted in an increase in the likelihood of survival.

2. Materials and Methods

The data represent a retrospective cohort study of 325 patients,194 of whom were male and 131 of whom were female, who were diagnosed with end-stage renal disease and receiving hemodialysis care and referred to public hospitals in Khartoum State such as Ahmed Gasim, Ibn Sina, Omdurman, Selma Center, Bahri, and Ribat during the period of time December 2005 and December 2010, and then they were followed until December 2015. Data was collected on age, date of disease diagnosis, survival status (dead or living per month), sex, marital status, education level, and occupation.

2.1. Data collection

Khartoum state is made up of three major cities: Khartoum, Bahri, and Omdurman. The study's data is collected from the most famous and well-known public hospitals in the three cities.

2.2. Inclusion criteria

Data on hemodialysis patients were collected from patient records. Who regularly visited the centers in the six public hospitals from December 2005 to December 2015, 1 to 90 years of aged patients were included

2.2. Exclusion criteria

Hemodialysis patients with acute renal disease, insufficient medical records, hemodialysis patients who have only stayed for a short period and people in emergency cases were also excluded.

2.3. Data analysis

AFT models were used to examine the relationship between one or more covariates and the application of AFT models was taken into account in this study. Some examples include Weibull, Exponential, log-normal, and log logistic. Time ratios are obtained by exponentiating the coefficients in AFT models. These time ratios will also be used to calculate the component change or the change in estimated survival time associated with a single unit increase in covariate. Significant variables with *p-values* less than 0.05 should be included in the final multivariate model structure, while non-significant variables can be excluded. Censor term refers to patients who remain alive until the end of the study, patients who have lost the last follow-up date with them and are no longer available to us, and patients who have had a successful transparent kidney; these categories have been considered the right-censored. The researchers used a multivariate approach to quantify and categorize the risk factors influencing these patients' survival. Different measurements of goodness of fit, such as (AIC), (BIC), and Cox-Snell residual, were used for model comparison. AIC and BIC have the lowest and highest values R^2. The residual plot of Cox-Snell was also used as an example of the optimal model, with the line closest to the bisector being the best.

2.3.1. Parametric models

Parametric models can be expressed in one Proportional Hazard (PH) formed in two ways, for example, when a one-unit change in an explanatory variable causes proportional hazard changes and another accelerated failure time (AFT). The second method occurs when a one-unit change in an explanatory variable results in a proportional change in survival time. The Weibull, Exponential, Gompertz, log logistic, lognormal, and gamma distributions are all commonly used. **[1, 2,12, 13, 14, 15]**

2.3.2. Parametric Accelerated failure time models

A general survival data model is the Accelerated Failure Time (AFT) model. In which the explanatory variables measured on an individual act multiplicatively on the time scale. The model for a group of patients with covariates (x_1, x_2,…x_p) can be expressed as the hazard function of the individual ith at a time.

$$h(t/x) = e^{-\eta(x)} h_0\left(t/e^{\eta(x)}\right) \qquad (1)$$

where

$$\eta(x) = b_1x_1 + b_2x_2 \dots + b_px_p)\}.$$

In a regression framework, η is an 'acceleration factor' that depends on the covariates can be parameterized as the exp(bx), where b is the parameter to be estimated from the data, The baseline hazard function, h_0 (t).

$$S(t/x) = S_0[t/\exp(\eta(x))] \qquad (2)$$

where S_0 is the baseline survival function at the time t, from equation (2), The ratio of two survival time is constant for any given survival probability. In order to illustrate this idea for a single covariate(x_1) of two degrees, for example x_1=0 for a standard treatment group and x_1=1, for a new treatment group, The survival probabilities S(t) for standard treatment group and for a new treatment groups are S_s(t) and S_n(t), respectively .Then the AFT model specifies that $S_s(t) = S_n(\eta t)$.The proportion of patients who are event-free in the standard treatment group at any time point is the same as the proportion of those who are event-free in the new treatment group at a time t /η. Where The η is an 'acceleration factor and positive constant, where η>1 and η<1, which represent situations where the length effect of survival is speed up and slowdown in the new treatment group compared with the a standard treatment group, respectively**[1,2,15,16.17].**

The AFT model is commonly rewritten as being log-linear with respect to time, giving

$$\log T_i = \mu + b_1x_1 + b_2x_2 + \cdots + b_px_p + \sigma \in \qquad (3)$$

T_i random variable associated with the lifetime of the individual in a survival study. In this model b_1,b_2,..b_p are unknown coefficients of the values of p explanatory variables, x_1,x_2,..x_p,and μ, σ are two further parameters, known as intercept and scale parameter, respectively. The quantity ∈ is a random variable used to model the deviation of the values of log T_i from the linear part of the model, and ∈ is assumed to have a particular probability distribution. In this formulation of the model, the b-parameters reflect the effect that each explanatory variable has on survival times positive values suggest that the survival time increases and negative values survival time decrease**[2,15,18,].** The AFT model is adapted by applying the maximum probability estimation approach using the Newton-Raphson iterative technique. For the sake of simplicity and ease of understanding, the time ratio (TR) called exponentiated regression coefficients [exp (b_p)] is recommended to report how HR is reported in models of proportional hazards. TR > 1 for a covariate means that the time to the occurrence is slowed down or extended, and TR < 1 for a covariate implies that earlier events are more likely to occur **[2, 15, 17, 18, 19, 20].**

2.3.2.1. Exponential and Weibull AFT model

If the T_i has a Weibull and Exponential distribution, then $\in_i$has a form of extreme value distribution known as the Gumbel distribution, according to the log-linear representation of the model in equation (3)**[2,12,21]**. The survivor function for this asymmetric distribution is

$$S_{\in i}(\epsilon) = \exp(-e^{\epsilon})$$

$\text{for } -\infty < \epsilon < \infty$

Amore general form of hazard function is such that

$$\mathbf{h(t) = \lambda\gamma t^{\gamma-1}}, \qquad (4)$$

The Survivor function is

$$\mathbf{S(t) = \left\{ -\int_0^t \lambda\gamma u^{\gamma-1}\, du \right\} = \exp(-\lambda t^{\gamma})} \qquad (5)$$

Consequently,γ and λ are called the shape and scale parameters,
Under the Weibull PH model, the hazard function of a particular patient is given by

$$\mathbf{h(t|x) = \lambda\gamma t^{\gamma-1} \exp(B_1x_1 + B_2x_2 + B_3x_3 + \cdots + B_px_p) = \lambda\gamma t^{\gamma-1} \exp(\acute{B}\, x)} \qquad (6)$$

The Weibull distribution has the AFT property. The Survival function is given by

$$\mathbf{S_i(t) = \left[-\exp\left(\frac{\log t - \mu - b_{\,1}x_1 - b_2x_2 - \cdots - b_px_p}{\sigma} \right) \right]} \qquad (7)$$

and the hazard function is given by

$$\mathbf{h_i(t) = \frac{1}{\sigma t} \exp\left(\frac{\log t - \mu - b_{\,1}x_1 - b_2x_2 - \cdots - b_px_p}{\sigma} \right)} \qquad (8)$$

Comparing the above two equation (6) and (7), we can easily see that the parameter λ, γ, B_P in the PH model can be expressed by the parametersμ, σ, b_p in the AFT model:

$$\mathbf{\lambda = \exp(-\mu/\sigma) \quad , \gamma = \sigma^{-1}, B_P = -b_p/\sigma}$$

2.3.2.3. Lognormal Distribution

A random variable T_i, representing the general accelerated failure time model, then has a lognormal distribution with parameters $\mu + \acute{b}x_p$ and σ.The survivor function of T_i is such that **[2,12].**

$$\mathbf{S_i(t) = 1 - \Phi\left(\frac{\log t - \mu - b_1x_1 - b_2x_2 - \cdots - b_px_p}{\sigma} \right)} \qquad (9)$$

The cumulative hazard function of Log-normal AFT model is

$$H_i = -\log S_i(t) = -\log\left(1 - \Phi\left(\frac{\log t - \mu - b_{1}x_1 - b_2x_2 - \cdots - b_px_p}{\sigma}\right)\right)$$

Where

$\Phi(.)$is the cumulative distribution function of a standard normal variable

2.3.2.4. Log –logistic distribution

A random variable $T_i$in the general accelerated failure time model, then has the Log logistic distribution withparameters$\theta - k\eta_i$ and k,where $\eta(x)$ is a linear combination of the values of b explanatory variables for ith individual**[2,12,17,21],** the survivor function is

$$S_i(t) = \frac{1}{1 + e^{\theta - k\eta(x)}t^k} \qquad (10)$$

and the hazard of death at time t for the ith individual is

$$h_i = \frac{e^{\theta - \eta(x)}\, k\, t^{k-1}}{1 + e^{\theta - k\eta(x)}t^k} \qquad (11)$$

For $0 \leq t < \infty, \gamma > 0.$

This hazard function decreases monotonically if$k \leq 1$, but if $k > 1$, the hazard has a single mode with shape parameter k and scale parameter θ.

Where

$$\theta = -\mu/\sigma, k = \sigma^{-1}$$

2.3.3. Selection Criterion

One of these criteria is the information criterion of Akaike (AIC), the Baysian Information Criterion (BIC) and the Cox-Snell Information Criterion (CSIC), the latter of which is a graphic rather than a mathematical criterion, many of the criteria used to choose the best model from different models deal with the same data for prediction in the future.

AIC: Comparisons may also be made on the basis of statistics between a variety of potential models which do not necessarily need to be nested **[2, 17,22, 23].**

$$AIC = -2(\log likelihood) + 2(P + K) \qquad (12)$$

Where P is the number of parameters, and K is the number of (excluding constant) coefficients in the model. For P=1, for P=2, for Weibull and Gompertz, for the exponential. The smaller the value of this statistic, the better the model, the better this statistic is known as Akaike's knowledge criterion.

BIC: The Baysian Information Criteria (BIC) is given by **[19, 24].**

$$\mathbf{BIC} = -2(\log \text{likelihood}) + (P + K) * \log(n) \qquad (13)$$

In the distribution, where P is the number of parameters, K is the number of coefficients and n is the number of observations. As the best-fit model, the distribution that has the lowest BIC value is considered.
a metric to test the goodness-of - fit of a regression model for proportional hazards. As a descriptive statistic for goodness of fit, Hosmer and Leme show propose the following**[20,25]**.

$$R_p{}^2 = 1 - \left\{ \exp\left[\frac{2}{n}(L_0 - L_P)\right] \right\} \qquad (14)$$

Where the log likelihood for the fitted model with p covariates is L_P, and L_0 is the log likelihood for model zero, the model without covariates is the log probability.

Cox Snell-Residual: The Cox-Snell Residuals can be used to check the quality of the model's fit **[19, 26]**, defined as the person with observed time t

$$r_{Ci} = \widehat{H}_i(t_i) = -\log \hat{S}_i(t_i), \qquad (15)$$

Where $\widehat{H}_i(t_i)$ is estimated cumulative hazard function, and $\hat{S}_i(t_i)$ is the estimated survivor function in equation are plotted against**[2].**

3. Ethical Considerations:
The study protocol was authorized by the ethics and research committees of the Ministry of Health of Khartoum (serial number: KMOH-REC-1-2020). Hospitals received informed consent.

4. Results
According to our findings, 325 hemodialysis patients were enrolled in this study.

This research included 325 hemodialysis patients. By December 2015, 52.3 % of patients had died, and 47.7 % were still alive, based on the results. The demographic characteristics of the targeted patients revealed that 59.7% were male and 40.3 % were female. According to the medical results, 88.9% of hemodialysis patients were normal, 11.1 % were irregular, 27.4 % had diabetes, and 72.6% did not have diabetes. 29.5 % were hypertensive, while 70.5 % were not. 89.8 % had both diabetes and hypertension, while 10.2 % did not have either. The frequency of dialysis per week was discovered to be two times (18.8 %) and three times (81.2%).Shrunken kidneys were found in 3.4 percent of the cases, while no shrunken kidneys were found in 96.6 percent of the cases.5.8 % had each other, and 94.2 % had no other. In regard to the qualitative variables such as age; the minimum age was 6years. The maximum age was 88years.The age in the first quartile was 46.03 years. The median age was 45years and the third quartile 75years.The median overall survival time was estimated at 84 months, and the trust level was found to be 95 percent (61-89), as shown in Figure 1, which clarified the overall survival curve of hemodialysis patients.

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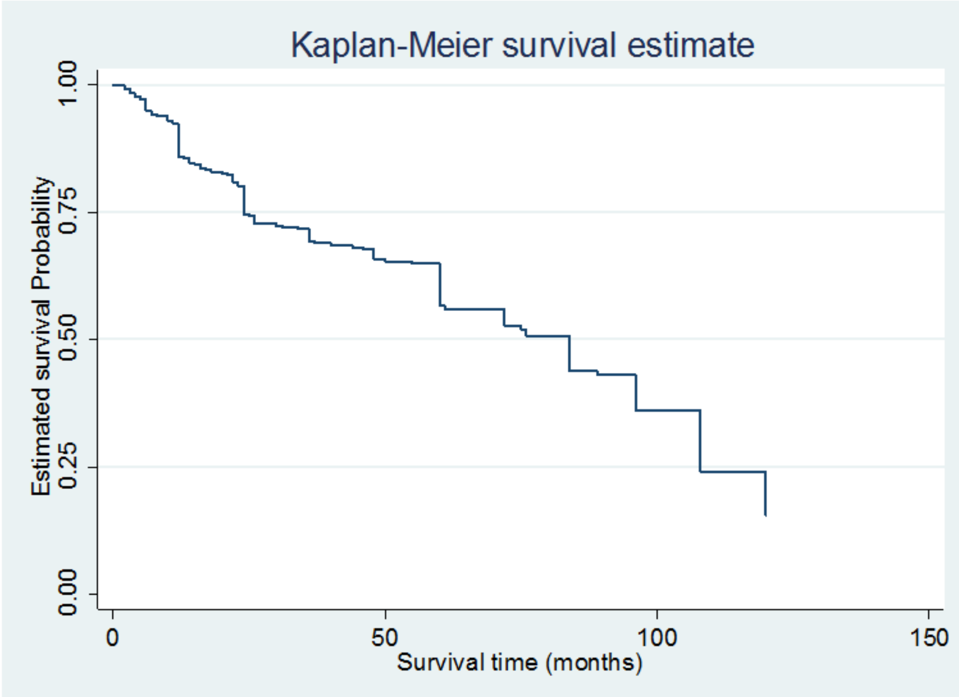

(Figure1)Kaplan-Meier to estimate survival function for hemodialysis patient

Table 1. Multivariate analysis for hemodialysis patients using Weibull and Exponential model.

variable	Weibull AFT					Exponential AFT				
	Coef (b_p)	TR {exp(b)}	P- value	95%CIfor TR		Coef(b_p)	TR {exp(b)}	P- value	95%CI for TR	
				CI_L	CI_U				CI_L	CI_U
Age	0.01	0.99	0.01	0.98	1.00	0.01	0.99	0.01	0.98	1.00
daily dialysis	-0.56	1.57	0.02	1.09	2.25	-0.54	1.72	0.02	1.1	2.68
hospital	-0.18	1.15	0.00	1.06	1.26	-0.16	1.18	0.00	1.05	1.31
diabetes mellitus	0.12	0.91	0.56	0.65	1.26	0.12	0.89	0.56	0.59	1.33
hypertension	-0.43	1.41	0.07	0.97	2.03	-0.41	1.51	0.08	0.96	2.39
diabetes mellitus +hypertension	0.13	0.9	0.63	0.58	1.39	0.15	0.86	0.58	0.5	1.47
shrunken kidneys	-1.83	4.33	0.07	0.87	21.45	-1.8	6.07	0.08	0.83	44.39
dialysis frequency per week	-0.39	1.36	0.03	1.03	1.8	-0.41	1.51	0.02	1.07	2.12
other	-0.88	2.02	0.07	0.95	4.27	-0.85	2.34	0.08	0.92	5.94
intercept	-3.44					-2.42				
shape parameter	1.25			1.1	1.41					
R^2	0.209					0.198				
AIC	669.47					678.95				
BIC	711.09					716.78				

Table 2. Multivariate analysis for hemodialysis patients usinglognormal and log logistic model.

variable	**lognormal AFT**					**log logistic AFT**				
	Coef (b_p)	TR {exp(b_p)}	P- value	95%CI for TR		Coef (b_p)	TR {exp(b_p)}	P - value	95%CI for TR	
				CI_L	CI_U				CI_L	CI_U

age	-0.01	0.99	0.24	0.99	1.00	-0.01	0.99	0.26	0.99	1.00
daily dialysis	0.74	2.11	0.00	1.36	3.26	0.79	2.20	0.00	1.39	3.50
hospital	0.18	1.20	0.00	1.09	1.32	0.17	1.19	0.00	1.08	1.31
diabetes mellitus	-0.19	0.83	0.35	0.56	1.23	-0.11	0.90	0.56	0.62	1.29
hypertension	0.20	1.22	0.35	0.81	1.83	0.30	1.35	0.13	0.91	2.01
diabetes mellitus +hypertension	-0.52	0.60	0.05	0.35	1.00	-0.45	0.64	0.10	0.38	1.08
shrunken kidneys	1.56	4.74	0.03	1.17	19.24	1.42	4.12	0.04	1.05	16.15
dialysis frequency per week	0.37	1.44	0.04	1.02	2.04	0.42	1.52	0.01	1.09	2.11
other	0.84	2.32	0.03	1.07	5.01	0.73	2.08	0.05	1.01	4.26
intercept	1.36					1.13				
shape parameter	1.12			1.01	1.25	0.63			0.56	0.71
R^2	0.209					0.214				
AIC	682.09					681.18				
BIC	723.71					722.80				

Coef; coefficient, TR=time ratio, CI=confidence interval, p-value significant at < 0.05 level of significance,
other= (Systemic lupus erythematous, tropical disease (malaria), Gout, cardiovascular disease, NSAID)

Based on a multivariate analysis, risk factors were evaluated to be significant compared to other Wald test variables (P-value< 0.05), including age, hospital, frequent dialysis, significant dialysis frequency per week in both Weibull and exponential models, except that age was negligible in other models.In addition to found the Shrunken kidneys and other significant in lognormal and logistic but other wasn't in log logistic. Under Weibull, exponential, lognormal, and logistical, TR variables find that the most relevant causes in patients with dialysis contribute to an elevated risk of mortality for patients, such as age, diabetes, diabetes + hypertension. In the other hand, other variables were observed; regular, hospital, hypertension, frequency of renal dialysis per week, shrunk and other; variables were found to have decreased risk of death. (see Table1and2).

According to Tables 1 and 2, Weibull has the lowest AIC and BIC (AIC = 669.47, BIC = 711.09) and the largest R^2 = 21%),where the value of R^2 is the same in all models except the exponential model, which has a 1% variance.
Figure 2shows the Cox-Snell residuals for four models. The survival model's fitness is more suited with the short variance of residuals from the straight line through the origin with a slope of 1. The Weibull AFT model is then superior to other AFT models based on parameters (AIC, BIC) and residual Cox-Snell.

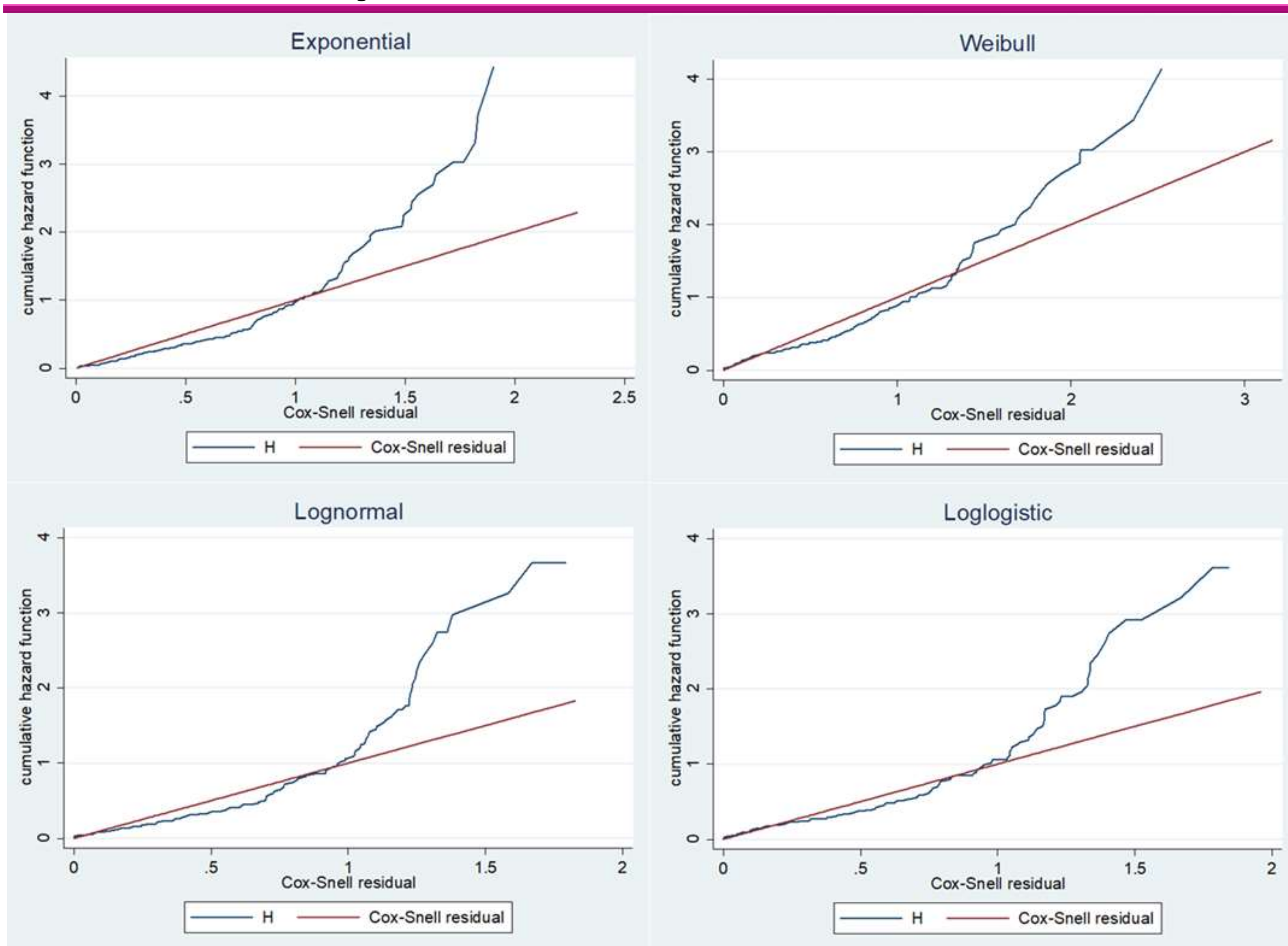

Figure 2.Cox-Snell residuals plot for multivariate models

5. Discussion

This study compares numerous parametric models to decide the best one for evaluating and examining the risk factors affecting patients with hemodialysis survival in public hospitals in Khartoum State using accelerated failure time models.

In this study, we extensively observed the medical histories of the patients in hospitals for the time leading up to a big event, such as death or survival.

The emphasis in the examination of survival outcomes is always on the chance or danger of dying at any point after the initial period. One rationale for modeling survival data is to determine which combinations of possible explanatory variables, particularly the kind of hazard function, explain the risk of death.

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A clear relationship between the predictors and the time of survival is postulated according to the AFT model, making its understanding simpler. Proportional hazard model care that causes the risk of death can be measured and the degree to

hich the hazard feature is impaired by other explanatory variables can be assessed. Another rationale for modeling the hazard function is that the hazard function itself is approximated by individuals**[2].**

An investigator can use the impact of factors of concern on the time to an occurrence after the distribution of the result has been determined. As previously stated, the effects of individual predictors in the AFT model are interpreted using time ratio (TR), where

TR is the acceleration factor. A time ratio greater than one, in contrast to HR, indicates that an occurrence is less likely to occur because an investigator must wait longer for the event to occur. Similarly, a time ratio of less than one indicates that the occurrence is more likely to occur **[13, 17].**

In this report, the multivariate analysis for four models (Exponential, Weibull, Lognormal, and Log Logistic) showed that several variables were both trivial and had important effects. Based on (Exponential, Weibull) models, we discovered that age, diabetes mellitus, and both diabetes mellitus and hypertension had a lower rate of survival under the accelerated failure time model, implying that they could influence survival in the multivariate model of this study. Other variables (regular, hospital, hypertension, shrunken kidneys, dialysis frequency per week, other) have a longer survival and have a direct effect on the hemodialysis patient's survival.

We discovered that regular, hospital, hypertension, shrunken kidneys, dialysis frequency per week, and other factors improved the survival time to the event, implying that an investigator would wait longer for the event to occur. In the other hand, with certain factors such as age, diabetes mellitus, both diabetes mellitus and hypertension, a time ratio shorter than one leads to a patient's time to death being accelerated.

Many factors were shown to be insignificant by multivariate regression. Weibull is the optimal model based on the outcomes based on parameters (AIC, BIC) , $R^2$and the Cox-Snell residual. Similar results were observed in previous research **[27]**.Age, diabetes mellitus, and hypertension were found to be important factors, although the frequency of dialysis each week was found to be negligible. Weibull was chosen as the most efficient model in a univariate and multivariate statistical study of hemodialysis patients (Exponential, Weibull, and Gompertz), but they were negligible in the multivariate. Another study **[28]** discovered that age, diabetes mellitus, and hypertension were negligible in Exponential and Weibull but clinically meaningful in Weibull and Exponential. The Weibull model was discovered to be the best fit among the parametric models of hemodialysis patients. In the four models tested in this analysis, only the hospital portion was relevant. Another research conducted in 2018 by Habibi et al. found that the log normal model offered the best match and was a good replacement for Cox regression in gastric cancer **[29]**. For studying survival data on Tuberculosis/HIV co-infected patients in Nigeria, Ogungbola et al (2018) used the Accelerated Failure Time (AFT) model. The results showed that the Weibull AFT model performed better with the studied evidence**[30]**.

In view of the Weibull multivariate model, which was a major value of the Wald test for various variables, like daily dialysis ($\hat{\beta}$ =-0.56,TR = exp^ $\hat{\beta}$ =1.57,P=0.02) hospital ($\hat{\beta}$ =-0.18,TR = exp^ $\hat{\beta}$ =1.15,P=0.00), age ($\hat{\beta}$ =0.01,TR = exp^ $\hat{\beta}$ =0.99,P=0.01),dialysis Frequency per week**(** $\hat{\beta}$ =-0.39, TR=exp^ $\hat{\beta}$ =1.36, P=0.03) ,when the ($P<0.05$) was achieved. That said, the approximate coefficient and time ratio were also important and had a clear impact on the survival of hemodialysis patients in this study.

In light of the preceding analysis, the multivariate model based on these variables was significant among the other models that were omitted from this research.

The bulk of medical records are unavailable, and there is a lack of documentation, making it impossible to ascertain the true cause of Sudan's disease epidemic. This is due to the fact that certain causes were not included in the patient's medical record, and therefore were not included in this analysis.

Further research in the root causes of kidney failure in Sudan should be conducted using the Cox Proportional Hazard model and the Accelerated failure time models.

Conclusion

In this article, AFT models were extended to hemodialysis patients at public hospitals in Khartoum State. The Weibull AFT model is the best for hemodialysis patient study model among the other one. Some variables, such as age, daily dialysis, hospital, and dialysis frequency per week, were important.The study revealed that certain variables, such as daily dialysis, were major factors.

Data availability

Underlying data available at Mekki, Reem (2019): data for hemodailysis.xlsx. figshare. Dataset.
https://doi.org/10.6084/m9.figshare.11105072.v1

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