SURVIVAL ANALYSIS OF PATIENTS ON DIALYSIS AT EKITI STATE UNIVERSITY TEACHING HOSPITAL ADO EKITI

BY

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ABSTRACT

Background

The increasing incidence and prevalence of chronic kidney disease (CKD) is a serious health challenge around the world. The need to examine the longevity of sufferers under care can never be over emphasized. This study therefore investigates survival experience and factors that may contribute to longevity of CKD patient aside the treatment obtained in the Hemodialysis Centre, Ekiti State University Teaching Hospital (EKSUTH), Ado-Ekiti.

Methods

Records of patients on dialysis at EKSUTH were reviewed. The data were collected by complete review of patient's clinical records. Descriptive statistics were used to describe social-demographic characteristics. Kaplan–Meier survival analysis was done to assess both short and long term survival. P-value of <0.05 was considered as statistically significant. The impact of six covariates on survival chances were separately investigated using Log-rank test. Also, the six covariates were further collectively examined using both Cox and Weibull models. Akaike Information Criterion was then employed for determination of a better model between them.

Results

The overall median survival time was 182 days. Only 66.3% of all the patients survived their 90th days after starting dialysis and approximately 25% survived to 366 days. Statistically significant hazard ratios for those patient with family history of chronic kidney disease was 0.45; 95% CI 0.23 – 0.90 and for those with urinary obstruction was 0.59; 95% CI 0.35 – 0.99. Model generated imply $\mathbf{h_i(t) = -5.1499\ exp\ \{-0.7850 Family\ His.\ Of\ CKD_i - 0.5353 Urinary\ status_i\}}$

Conclusion

Survival rate of chronic kidney disease (CKD) patients in Ekiti State University Teaching Hospital (EKSUTH) was better than those reported in others sub-Saharan Africa, but lower than the rate from developed countries. Out of the entire explanatory variables investigated for their influence on survival chances during dialysis, only family history of chronic kidney disease and urinary status were statistically significant among variables considered. Though, age-group of patients at start of dialysis was also statistically significant when separately investigated. This study hence recommends appropriate attention to be paid to those with no family history of CKD and urinary obstruction at start of dialysis while evaluating patient for CKD.

Keywords: Chronic Kidney Diseases, Dialysis, Cox Proportional Hazard model, Weibull model

Words count = 341

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DEDICATION

This Dissertation is dedicated to Jehovah.

CERTIFICATION

I certify that this project was carried out under my supervision by Adekoya, Joshua Inubile in the Department of Epidemiology and Medical Statistics (EMS), Faculty of Public Health, College of Medicine, University of Ibadan.

Sign..... **Date**.11-04-2013.....

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ACRONYMS

CKD	Chronic Kidney disease
EKSUTH	Ekiti State University Teaching Hospital
AIC	Akaike Information Criterion
KM	Kaplan Meier
WKD	World Kidney Day
LOG	Natural Logarithm
MOP	Medical Outpatients departments
BP	Blood pressure
DM	Diabetes mellitus

CHAPTER ONE

INTRODUCTION

1.1 General background:

Globally, the prevalence of renal disease at pandemic rate has become a matter of great concern. It is estimated that 1 out of 10 people is afflicted by chronic kidney disease (CKD). This means that more than 500 million people worldwide are suffering from the disease. Renal disease prevalence also increases with age; one out of five men between 65 and 74 years has renal disease. The prevalence in women of similar age group is estimated at 1 in 4 (World Kidney Day, 2013).

Thirty six million, eight hundred thousand Nigerians (including Ekiti people) are suffering from kidney disease at different stages. With this figure, it means that one in seven (1/7) Nigerians is suffering from some form of kidney disorder or another (World Kidney Day, 2013). The statistics (two years later) will be more worrisome, due to its persistent increasing trend as revealed by many previous publications. Most patient that cannot afford dialysis die eventually of heart disease. Maintain dialysis cause between N100, 000 to N120, 000 per week which most families cannot afford in Nigeria (Awobusuyi, 2015).

Dialysis is a procedure for removing waste and excess water from the blood; which is primarily used as an artificial replacement for lost kidney function in people with renal failure. Dialysis is used for treating patients with acute kidney injury, previously acute renal failure or chronic kidney diseases (CKD). Kidney is an important organ of the body for maintaining internal balance. Problem occurs when the kidney continuously malfunction for a period more than three months.

Survival analysis as employed in this study is designed to handle time-to-event data, taking into account censored cases. These are cases where the event of interest has not occurred yet at the end of the study or before lost to follow-up or it has occurred due to some other causes. The

degree of censoring can affect the reliability of the results and there are recommendations for the maximum percentage (%) of censoring allowable in a group along with sample size.

Survival analysis looks at how long it takes for an event to happen. The event may be either positive or negative outcomes such as recovery or failure respectively. Analysis of survival data needs special consideration compared to other data for two reasons, the censored nature of a proportion of the data and also the fact that it does not tend to follow a normal distribution. "Survival data arises when the aim is to study the time elapsed from some particular starting point to the occurrence of an event (Marubini and Valsecchi, 2004).

This study was a five-year retrospective review of all patients with CKD who received treatment at the Hemodialysis centre of EKSUTH. The record of all patients with a diagnosis of CKD who required dialysis therapy was reviewed within the period under study.

This study examined the survival chances among CKD attending the dialysis centre at EKSUTH, and also generated a mathematical survival model that would predict the absolute chances of survival with dialysis patients. It also investigated how variables such as age, sex, hypertension, diabetes, family history CKD and urinary obstruction affect longevity of sufferers, apart from the effect of treatment. The specialty in this study is using both the commonly used non-parametric, and the more rigorous parametric survival analytical methods, to analyze dialysis patient's survival data which allows comparison that facilitated results with precision.

1.2 Statement of Problem:

The recent upsurge in case of kidney failure in Ekiti can be attributed to unhealthy life-style (Olomojobi, 2015). It is estimated that about 36.8million Nigerians (Ekiti people inclusive) are suffering from kidney disease at different stages. Meaning, one in seven (1/7) Nigerians is suffering from some form of kidney disorder or another (World Kidney Day, 2013). Most of the reviewed works has not examined the role of some important explanatory variables that need to be considered.

Cox proportional hazard regression has been the usual model for analyzing survival data but more precise results can be achieved when the actual distribution of the survival time is known and used in the modeling. Literature is scanty on the study of survival chance of dialysis patients

in Ekiti state, south-west, Nigeria. This study therefore provides a scholarly impetus to improve the study of survival chance of dialysis patients in Ekiti state.

1.3 Rationale for the study:

The rationale for this study is to increase peoples' awareness on the survival chances of CKD patients with the aim of reducing the rising trend of the case. This study will also help in examining the efficiency of the medical treatment in the hospital in managing the dialysis patients.

1.4 Objectives of the study:

To measure the survival experience of chronic kidney disease patients in Ekiti State University Teaching Hospital (EKSUTH).

The specific objectives are to:

1. To determine the 4-week, 12-week, 26-week and 52-week survival probabilities of Haemodialysis patients.
2. To model the effect of factors such as age, sex, blood pressure, family history of CKD, diabetes and urinary obstruction on the risk of failure during treatment.
3. To compare the use of Cox-proportional hazard model and Weibull model in order to achieve more precise model.

CHAPTER TWO

LITERATURE REVIEW

2.0 Chronic Kidney Diseases

Chronic kidney disease (CKD) includes conditions that damage kidneys and decrease their ability to keep healthy by doing the jobs listed. If kidney disease gets worse, wastes can build to high levels in blood and be sick. One may develop complications like high blood pressure, anemia (low blood count), weak bones, poor nutritional health and nerve damage (Collins et al, 2009; McCullough et al, 2007). Also, kidney disease increases the risk of having heart and blood vessel disease. These problems may happen slowly over a long period of time. Chronic kidney disease may be caused by diabetes, high blood pressure and other disorders (Jafar, 2006). Early detection and treatment can often keep chronic kidney disease from getting worse (Barnes JN, et al. 1992). When kidney disease progresses, it may eventually lead to kidney failure, which requires dialysis or a kidney transplant to maintain life (National Kidney Foundation, 2015).

The cost of management of end stage kidney disease is prohibitive and tasks the economies of even the rich countries. Unfortunately in Nigeria, poverty, inadequate health facilities, lack of subsidy for medical treatment conspire to present a gloomy picture (World Bank, 2009; Nwakoma, 2007). The trust of management of kidney disease should focus on prevention (Chinwuba, 2011)

2.1 CKD as a public Health problem

It has been made known by many studies (Chadban et al, 2003; DE ZEEUW et al, 2005) that chronic kidney disease is a world-wide public health problem. In Sub-Saharan Africa, there is a rising incidence and prevalence of kidney failure, with poor outcomes and high cost. There is an even higher prevalence of earlier stages of chronic kidney disease. Increasing evidence, accrued in the past decades, indicates that the adverse outcomes of chronic kidney disease, such as kidney failure, cardiovascular disease, and premature death, can be prevented or delayed (Laura, et al. 2008). Earlier stages of chronic kidney disease can be detected through laboratory testing. Treatment of earlier stages of chronic kidney disease is effective in slowing the progression toward kidney failure. Initiation of treatment for cardiovascular risk factors at earlier stages of chronic kidney disease should be effective in reducing cardiovascular disease events both before

and after the onset of kidney failure. Unfortunately, chronic kidney disease is ''under-diagnosed'' and ''under-treated'' in the Sub-Saharan Africa, resulting in lost opportunities for prevention (Bosan, 2007).

2.2 Incidence and factors associated with of CKD in Sub-Saharan Africa

Chronic kidney disease is at least 3-4 times more frequent in Africa than in developed countries. Hypertension affects approximately 25% of the adult population and is the cause of chronic kidney failure in 21% of patients on renal replacement therapy in the South African Registry. The prevalence of diabetic nephropathy is estimated to be 14%-16% in South Africa, 23.8% in Zambia, 12.4% in Egypt, 9% in Sudan, and 6.1% in Ethiopia. The current dialysis treatment rate ranges from 70 per million populations (pmp) in South Africa to < 20 pmp in the most of sub-Saharan Africa. The transplant rate in Africa averages 4 pmp and is 9.2 pmp in South Africa (Naicker, 2009).

The goal for sub-Saharan Africa should be to have a circumscribed chronic dialysis program, with as short a time on dialysis as possible, and to increase the availability of transplantation (both living related and cadaver) and promotion of prevention strategies at all levels of health care. Screening for kidney disease in high-risk populations example, patients with hypertension and diabetes mellitus and a family history of kidney disease, should be instituted as the first step in kidney disease prevention in developing countries (Naicker, 2009; World Kidney Day, 2013).

2.3 Incidence of CKD in Ekiti

No data yet. However, 36.8 million Nigerians (Ekiti people inclusive) are suffering from kidney disease at different stages. Meaning, one in seven (1/7) Nigerians is suffering from some form of kidney disorder or another (World Kidney Day, 2013).

2.4 Survival Analysis

Survival analysis is concerned with statistical models and methods for analyzing data, representing life times, waiting times or more generally times to the occurrence of some specified event. Outcome variable of interest is time until an event occurs. Such data denoted as survival data, can arise in various scientific fields including medicine, engineering, and demography (Read, et al. 1998). Moreover survival data can attain from laboratory studies of

animals or from clinical studies of humans who experience acute diseases. Survival data can comprises on survival time, response given treatment, and patient distinctiveness, allied with response and survival (Kleinbaum and Klien, 1996).

2.5 Censored Data

A sample or observation is supposed to be censored, while by accident or design, the measurement of a random variable under study remains unobserved for several items in the sample. e.g., in a study, leukemia patients observed until they quit from state of the remission, if the period of study completed whereas the patient is still in remission (with no event) in that case the patient's survival time is referred as censored. And in this situation the survival time of individual is equal to the follow up period of that individual. However if the patient quit from remission, later than the study bring to an end, the total survival time of patient cannot be identified (Kleinbaum and Klien, 1996). When time-related variables take on in research, for example survival and recurrence, the researchers do not know the results for all patients after the time of study is fulfilled, consequently these results are known as censored (Dawson and Trapp, 2004). For those individuals who remain alive at the end of study or whose survival status was unidentified the Survival time cannot be determined and this sort of observations are referred to as censored observations. The individuals who remain alive at the end of study are called as withdrawn alive and whose status could not be evaluated because they moved away or refuse to become a part of experiment, described as lost to follow-up (Forthofer and Lee, 2006). Patients do not usually commence treatment or come into the study simultaneously. When the entrance of patients in the study is not at the same time and numerous patients are remaining in the study after the period of follow up, the data is considered as progressively censored or doubly censored (Dawson and Trapp, 2004). When the end point of interest has not so far occurred and personnel's accurate survival time partially known at the right side of the follow-up period and study come to an end then this sort of data is known as Right-censored data (Ralston and Wilf, 1967). Moreover, data may be left-censored. In left-censored data the survival time of a person is partially known at the left side of the follow-up period for that person.

2.6 Ways of analyzing survival data

Parametric:

Overview

Survival analysis is the study of time-to-event data. Its terminology traces back to medical studies where the event of interest was death and to industrial studies where the event of interest was failure, such as burn-out of a motor or bulb. The objective was to understand the correlates of survival, hence survival analysis.

Survival analysis may be parametric or semi-parametric. This volume of the Statistical Associates "Blue Book" series treats parametric survival analysis. "Parametric" means that an essential parameter, the baseline hazard function, must be specified by the researcher in advance. The baseline hazard function defines the chance of experiencing the event of interest (the "hazard", which traditionally was death or failure) when other predictors in the model are held constant. Positing the correct baseline hazard function is quite challenging, often leading the researcher to rely on semi-parametric survival analysis, which does not require this. Cox regression is the prime example of semi-parametric survival analysis and is treated in a separate volume.

A related term is "event history analysis," which is also called duration analysis, hazard model analysis, failure-time analysis, or transition analysis. Event history analysis is an umbrella term for procedures for analyzing duration-to-event data, where events are discrete occurrences. "Event history" studies have been common in the study of international relations, where events may be wars or civil conflicts. Many of the earlier conflict studies utilized Weibull and other parametric survival analysis models and therefore event history analysis is often seen as a type of parametric survival analysis.

Coleman (1981: 1) defined event history analysis in terms of three attributes: (1) data units (ex., individuals or organizations) move along a finite series of states; (2) at any time point, changes (events) may occur, not just at certain time points; and (3) factors influencing events are of two types, time-constant and time-dependent. Event history models focus on the hazard function, which reflects the instantaneous probability that the event of interest will occur at a given time, given that the unit of analysis has not experienced the event up to that time. While duration until

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death or failure was the classic examples, duration of peace until the outbreak of war was an example in international relations. In the last few decades, survival analysis has been applied to a wide range of events, including "hazards" with a positive meaning, such as duration until the event of adoption of an innovation in diffusion research. Other applications include study of longevity of trade agreements, strike durations, marriage durations, employment durations, and innumerable other subjects (Garson, 2012).

Non Parametric:

Nonparametric statistics are statistics not based on parameterized families of probability distributions. They include both descriptive and inferential statistics. The typical parameters are the mean, variance, etc. Unlike parametric statistics, nonparametric statistics make no assumptions about the probability distributions of the variables being assessed. The difference between *parametric* models and *non-parametric* models is that the former has a fixed number of parameters, while the latter grows the number of parameters with the amount of training data. Note that the *non*-parametric model is not *none*-parametric: parameters are determined by the training data, not the model.

Non-parametric methods are widely used for studying populations that take on a ranked order (such as movie reviews receiving one to four stars). The use of non-parametric methods may be necessary when data have a ranking but no clear numerical interpretation, such as when assessing preferences. In terms of levels of measurement, non-parametric methods result in "ordinal" data.

As non-parametric methods make fewer assumptions, their applicability is much wider than the corresponding parametric methods. In particular, they may be applied in situations where less is known about the application in question. Also, due to the reliance on fewer assumptions, non-parametric methods are more robust.

Another justification for the use of non-parametric methods is simplicity. In certain cases, even when the use of parametric methods is justified, non-parametric methods may be easier to use. Due both to this simplicity and to their greater robustness, non-parametric methods are seen by some statisticians as leaving less room for improper use and misunderstanding.

The wider applicability and increased robustness of non-parametric tests comes at a cost: in cases where a parametric test would be appropriate, non-parametric tests have less power. In other words, a larger sample size can be required to draw conclusions with the same degree of confidence.

Up till now, physicians have done few descriptive researches related to causes of Kidney failure and quality of life of Dialysis patients, but there is rare chance of any documented statistical inferential work about survival of these patients, done by statisticians in Ekiti. Most of the reviewed works has not examined the role of some important explanatory variables that need to be considered.

CHAPTER THREE

METHODOLOGY

3.0 STUDY LOCATION

3.1.1 Haemodialysis Centre, EKSUTH, Ado-Ekiti

The centre was established in August, 2010 with the assistance of MTN foundation in conjunction with ADCEM pharmaceutical company both who provided instruments and equipment. EKSUTH management provided building, the personnel and ancillary items for operations like consumables. There was a cordial agreement between MTN and EKSUTH on operation modality. MTN further subsidized the cost of a dialysis at the centre to N15, 000 only till present to make the service considerably affordable to sufferers.

3.1.2 Source of patients in the centre

Patients are recruited into the centre from different sources. These includes

1) Medical Outpatients department (MOP)
2) Medical wards (Adults Male, Adults Female and Children).
3) Other wards in EKSUTH and
4) Referral from other hospitals in Nigeria.

3.1.3 Treatment and follow up

All confirmed CKD patients were placed under dialysis and drugs. Dialysis sessions are supposed to be observed for at least twice in a week depending on patient condition. End stage of CKD patients are advised to go for transplantation. Patient who did not present him or herself for dialysis when ought to have done so is always call on phone to ascertained their problems and status.

3.1.4 Clinic Medical Records (manual)

Vital medical information about patients as contained in different clinical forms are collated and kept in their hospital case notes which are numbered with either serial or non-serial numbers, the former is for outpatients while the later for inpatients. Patients case note are then temporary safe-

keep in shelve at the centre and later transferred to the central library of health information management department of the hospital.

Different clinical record documents

The following clinical record documents are used at the centre. These are

Laboratory investigation forms.

Scan report form.

X-ray repot sheet.

Haemodialysis chart.

3.2 Study Design

This study is based on follow up data within the period of 5 years (August 2010 to December 2014) of all the patients dialyzed at the Haemodialysis, EKSUTH, Ado-Ekiti. The analyzed data were extracted from relevant clinical forms of the Haemodialysis centre.

3.3 Exclusion criteria

Patients whose follow up data were not properly recorded in the forms seen were excluded from the study.

3.4 Sample size determination

Total number of patients that were dialyzed between August 2010 and December 2014 who had complete records was considered for the study. For this study, data on 107 patients was captured for the analysis.

3.5 Data collection

Variables that were extracted for each patient includes

Date of first dialysis session.

Age of the patient

Sex of the patient

Blood pressure (BP) of the patient at commencement of dialysis.

Diabetes (DM) status of the patients.

Patient family history of CKD.

Patient urinary obstruction status.

Last date of dialysis session.

Status of patient after last dialysis.

Patient time.

Date of first dialysis session: This is the day the patient commenced dialysis. This is the treatment starting point for the patient.

Age of the patient: This is the patient age at first dialysis. Age was categorized into two group < 60 and >/=60 using 60 years as cut off point been the general retirement age in Nigeria. This was used in Cox proportional and Weibull analysis to determine whether age is a predictor of survival time.

Sex of the patient: Survival time by female and male gender was also determined. This was used in Cox proportional and Weibull analysis to determine whether gender is a predictor of survival time.

Blood pressure (BP) of the patient at commencement of dialysis: Blood pressures were examined if it could determine survival time by using Cox proportional and Weibull analysis. Blood pressure classification style that was adopted is as tabled below

Jnc 8 classification of Hypertension

BP	SBPmmHg	DBPmmHg
Normal	<120	<80
Prehypertension	120-139	80-89
1st stage HTN	140-159	90-99
2nd stage HTN	>/= 160	>/= 100

Patient family history of CKD: History of CKD in patient family were also examine if it could explained survival time by using Cox proportional and Weibull analysis.

Patient urinary obstruction status: Cox proportional and Weibull analysis used to verify if survival time is also a function of having urinary obstruction.

Last date of dialysis session: This is the date of which the last dialysis for the patient was done in the centre. This is the treatment end point for the patient.

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Status of patient after last dialysis: This is the treatment outcome of the patient after the last dialysis session. The status may be failure (death) or censor

Patient time: This is the time a patient spends in the study from the time of first to the last dialysis.

3.6 Data management and Data analysis

Data analysis was performed with STATA version 12. Some of the results were later presented in form of Charts and table using Microsoft Excel Windows 2007.

Bivariate analysis was conducted using nonparametric technique; Kaplan-Meier Product Limit Method (Kaplan-Meier, 1958) was employed in estimation of the survival functions and hazard rates of the survival data. Also both Log-Rank Test and Wilcoxon (Breslow) test was used for the comparison of survival functions.

Cox's proportional hazard regression (Multivariate analysis) was initially used to model the relationship between the survival time and explanatory variables such as age, sex, hypertension, diabetes, family history and urinary obstruction. This statistical modeling tool which is semi-parametric was employed because in biomedicine, prior knowledge about the distribution of survival functions is rarely available.

Cox Proportional Hazard model implies; $\mathbf{y(t) = y_0(t)\ exp(\beta x_i)}$ where

$\mathbf{y(t)}$ is the hazard at time t, $\mathbf{y_0(t)}$ is the baseline hazard function,

$\mathbf{x_i}$ is the set of independent variables, $\boldsymbol{\beta}$ is the vector of coefficient of the independent variable x_i

And later on the other hand, that is, parametric technique; the distribution of the survival data which may follow any of Exponential, Generalized Gamma, Logistic or Weibull was determined. The dialysis survival data used in this study follows Weibull distribution which enabled the fitting of the probability distribution of real life time data of dialysis patients.

Therefore to be able to choose the better model between Cox proportional and Weibull, Akaike Information Criterion (AIC) was employed. Model that has AIC estimate with smallest value is considered to be more precise.

Study Variables and data analysis

Variables
Age (years): Age of patients **Age (years)** < 60 >/= 60
Sex: Sex of the dialyzed patients (1=Male, 2=Female)
Blood pressure (BP) of the patient: (1=Normal, 2=Prehypertension, 3=1st stage hypertension & 4=2nd stage Hypertension)
Diabetes (DM) status of the patients: (1=Diabetic, 0=Not Diabetic)
CKD history in patient's family: (0=No, 1=Yes)
Patient urinary obstruction status: (0=Obstructed, 1=Unobstructed)
Lost to follow up fraction: = total patients lost / Total patients recruited
Survival Analysis: Measurement of survival experience **Time of Origin:** Time of first dialysis. **Patient Status as at 31/12/2014:** 0=Censored, 1=Death. **Endpoint:** Physical Death of patient. **Censored time (Alive, Relocated or death not related to CKD):** on or before 31/12/2014. Person Week: This is the time that the patient spends in the study from start of dialysis to endpoint or censored time (patient time).

Kaplan-Meier Estimator

Widely used and recommended technique in survival analysis which adequately takes care of censored data is the Kaplan-Meier (K-M) method. 'K-M is the most popular in developing survival function (Collect, 2003). The method which is suitable for this study (Maryam, et al. 2012) is used to measure the fraction of subjects living for a certain period after the start of treatment. It is applied by analyzing the distribution of patient's survival times following their recruitment to a study. In analyzing the survival functions that are dependent on time are of particular interest; the survival function [S(t)] and hazard function [h(t)]. K-M graph is achieved by plotting S(t) values against duration of time (t). The non parametric estimates of S(t) are step functions. S(t) is the probability of surviving at least to time t. h(t) is the conditional probability of dying at time t having survived to that time. h(t) is otherwise called instantaneous death after time t (Maryam Siddiqa et al. 2012).

The K-M estimate of the survivor function S(t) can be written as:

$$S(t) = \prod_{j=1}^{k} p_j$$

for K = 1, 2, ------, r

where $p_j = (n_j - d_j)/n_j$ is the estimated probability that an individual survives through the time interval which begins at $t_{(j)}$,

j = 1, 2, -----, r

And for hazard function [h(t)]

If there are d_j deaths at the j-th death time, t_j,

j = 1, 2 ------r and n_j at risk at time $t_{(j)}$, the hazard function in the interval from $t_{(j)}$ to $t_{(j+1)}$ can be estimated by

$$h(t) = (d_j)/(n_j w_j) \quad \text{for } t_{(j)} \leq t < t_{(j+1)}$$

where $w_j = t_{(j+1)} - t_{(j)}$

Median survival time

Since the distribution of survival times tends to be positively skewed, the median is the preferred measure of the location of the distribution (Maryam, et al. 2012 and Tamiru, et al, 2013). The median survival time is obtained from survivor function: *median survival time is the time beyond which 50% of the individuals in the population are expected to survive.* It is given by that value t(50) which is such that $S\{t(50)\} = 0.5$

Since the non parametric estimates of S(t) are step functions, the estimate median survival time t(50) is defined as the smallest observed survival time for which the value of the estimated survivor function is less than 0.5. i.e. $t(50) = \min\{/S(t_1) \leq 0.05]$, where t_i is the observed survival time for the i-th individual i = 1, 2, -------n.

Bivariate analysis using Log-Rank or Wilcoxon (Breslow) test

Both Log-Rank and Wilcoxon (Breslow) test compares the over survival experience of two groups of interest. The null hypothesis tested here is that the risk of death/ event is the same in all the groups (Tamiru, et al, 2013). That is

Ho: S1(t) = S2(t) versus HA: S1(t) ≠ S2(t)

Meaning, "is overall survival different between the groups?" The test statistic is compared with a X^2-distribution with 1 degree of freedom.

Log-rank: is more sensitive to later survival difference.

Wilcoxon: is more sensitive to early survival difference.

Both: compute difference between what is observed at each event time and what would be expected under the null hypothesis.

- These difference are aggregated across all event times into one overall "distance" measure (i.e., how far sample curve differ from null after accounting for sampling variability).
- The Wilcoxon and Log-rank test aggregate these event-time specific differences slightly differently.
- Both tests give a P-value and generally these P-values are similar.

~~Neither:~~ Give overall measure of association (like a relative risk etc) or confidence interval.

The null hypothesis that there is no difference in the survival experiences of individuals between the two groups at time $t_{(j)}$ can be tested by the usual χ^2 test. This test can be repeated for each of the death times. Then we need to find a way to summarize this series of test by combining the information from the r individual 2 x 2 tables. A method of doing this is the Mantel - Haenszel procedure; if the marginal totals in the table are regarded as fixed,

- Then the four entries in the table are solely determined by the value of d_{1j}

- We can then regard d_{1j} as a random variable with hypergeometric distribution with mean $e_{1j} = n_{1j}d_j/n_j$ and variance $v_{1j} = n_{1j}\, n_{2j}\, d_j\, (n_j - d_j)/\{n_j^2(n_j - 1)\}$.

On the null hypothesis that the risk of death is the same in the two groups, then the expected no. of deaths in Grp 1 at time $t_{(j)}$ is $E(d_{1j}) = e_{1j} = n_{1j}\, d_j/n_j$

The difference between d_{1j} and e_{1j} is evidence against the null hypothesis

- the log rank test is the combination of these differences over the total number death times, r, in the two groups

- the resulting statistic is $U_L = \sum_{l=j} (d_{1j} - e_{1j})$

$= \sum d_{1j} - \sum e_{1j}$

= difference between the total observed and expected deaths in Group 1

- U_L has mean zero since $E(d_{1j}) = e_{1j}$

since the death times are independent of one another

$\text{Var}\,(U_L) = \sum \text{var}\,(d_{1j})$

$= \sum_{j=1}^{r} V_{1j} = V_L$

- it can be shown that U_L has approximate normal distribution when the number of death times is not too small

- it then follows that $U_L/\sqrt{V_L}$ is approx $N(0,1)$

or U_L^2/V_L is χ_1^2

- the test based on this statistic is known as the Log rank test

Multivariate analysis using Cox proportion hazard models

In the analysis of survival data, interest centres mainly on the risk of hazard of death at any time after the time of origin of the study (Usman, 2014) as applicable to this study. Modelling of hazard function directly as dependent variable allows the determination of which combination of potential explanatory variables affect the hazard function as distinct from the effect of treatment, thus as applicable to this study

$$h_i(t) = h_0(t) \exp\{\beta_1 \text{Age group}_i + \beta_2 \text{Sex}_i + \beta_3 \text{Blood pressure}_i + \beta_4 \text{Urinary status}_i + \beta_5 \text{Diabetes status}_i + \beta_6 \text{Family History of CKD}_i$$

where, Hazard function (ψ) = exp (β). Therefore ln (ψ) = β.

The independent variables were those that are statistically significant in the Log-rank test. They were the variables that have impact in the longevity of patients under treatment.

The base line yo(t) is the hazard function for an individual for whom the value of all independent variable are zero. Dependent variable y(t) = Hazard of death at time t.

Determination of distribution of survival pattern

Among other distributions, Weibull which was discussed by Weibull himself in 1951 has having broader application to various failure situations was assumed and later confirmed to be appropriate for data under study. The Weibull model is a generalization of exponential distribution. However, it does not assume a constant hazard rate like exponential model (Elisa and John, 2003).

Weibull distribution, $\lambda(t) = \alpha\lambda.t^{\alpha-1}$, $S(t) = e^{-\lambda t\alpha}$ where λ is mortality rate at time t.

Note this model allows:

Constant hazard: $\alpha = 1$

Increasing hazard: $\alpha > 1$

Decreasing hazard: $\alpha < 1$.

Since $\text{LogS}(t) = -\lambda t^{\alpha}$, so $\text{Log}\{-\text{logS}(t)\} = \text{Log}\lambda + \alpha\text{Log}(t)$

A (approximate) straight line in the plot of $\text{Log}\{-\text{logS}(t)\}$ vs Log(t) indicates a Weibull model (Daowen, 2005).

Akaike Information Criterion (AIC)

Akaike Information Criterion (AIC) as appropriate for this study (Usman, 2014) is a technique that measures the goodness of an estimated statistical model and selects a model from a set of model. The chosen model is the one that I expected to minimize the difference between the model and the truth. Given a set of data, several competing model may be ranked according to their corresponding AIC, and the one having the smallest AIC is the best (Elisa and John, 2003). AIC was the first model criterion to gain wide spread acceptance. AIC was introduced in 1973 by Hirotogu Akaike as an extension of the maximum likelihood principle. AIC is given by the formula:

AIC = -2{ln(likelihood)} + 2k where

Likelihood = the probability of data in a given model.

K = the number of the parameter in the model.

3.7 Ethical approval

Approval was obtained from the management of EKSUTH Haemodialysis centre to extract the data.

3.8 Study limitations

The end-point ascertainment is not very firm for the patients, since the information we have is their relatives. Seven (7) patients whose names also appeared in the Hemodialysis registered but some of their vital records are missing were excluded from the study.

Due to confidentiality of the patient's data it took time to get approval from the management of EKSUTH Haemodialysis centre to extract the data. Also, the result of the analysis is not to be published without going through the Ethical Review Committee of EKSUTH.

3.9 Strength of the study

The institution chosen as the site has a considerable good structure for record keeping system where information sought or observed from the patients are properly safe-keep from time-to-time. This study could be generalized for the people of Ekiti and its environs because EKSUTH was the only teaching hospital covering others neighboring states as at the study time.

This study has provided information on the survival experience among a fairly large population of patients treated with dialysis at Haemodialysis Centre of EKSUTH. The study also reveals some explanatory variables that have their impact on longevity of CKD patient.

CHAPTER FOUR

RESULTS

4.0 Distribution of the reviewed CKD patients data according to years and sex

Out of 114 CKD patient's captured as at 31st December, 2014 been patients dialyzed in the Haemodialysis Centre, EKSUTH from 2010 to 2014; seven (7) patients whose vital information were not properly recorded were excluded from the study. A total of 107 patients (Table 4.0) who have complete record were included in the study. By sex distribution, 107 where 74 (69.2%) and 33 (30.8%) were male and females respectively. This shows that higher numbers of males were registered than females. Year 2013 patient's load was the highest (46.7%) between this study period.

Out of the 107 patients, 40 (37.4%) were censored due to been alive up till or after the study time or were lost to follow up, 67 (62.6%) patients were reported to have die as a result of CKD.

Table 4.0: Distribution of the reviewed CKD patients data according to years and sex

Year	Number Recruited		
	Males	Females	Total
2010	3 (100%)	0 (0.0%)	3 (2.8%)
2011	10 (76.9%)	3 (23.1%)	13 (12.1%)
2012	9 (75.0%)	3 (25.0%)	12 (11.2%)
2013	36 (72.0%)	14 (28.0%)	50 (46.7%)
2014	16 (55.2%)	13 (44.8%)	29 (27.1%)
Total (2010 - 2014)	74 (69.2%)	33 (30.8%)	107 (100%)

4.1 Demographic characteristics of the patients

Table 4.1 shows the demographic characteristics of the patients. The age of the patients range from 21 – 89. The mean age of the patients was 51 ±15.4 years. The largest number of patients falls between age group 50 -59 years (22.3%). Male sex were 74 (69.2%) and female 33 (30.8%). Most of the patients (43.9%) were secondary school holders and business men (43.9%) constituted the highest proportion of their occupations.

Table 4.1: Social Demographic Characteristics of chronic kidney disease patients

	Count	Percentage (%)
Age Group (Years):		
20 – 29	8	7.8
30 – 39	22	20.4
40 – 49	20	18.7
50 – 59	24	22.3
60 – 69	20	18.7
70 & above	13	12.1
All (21 - 89)	107	100.0
Sex:		
Male	74	69.2
Female	33	30.8
Occupation:		
Civil Servant	16	15.0
Business men	47	43.9
Farmer	17	15.9
Artisan	9	8.4
Others	18	16.8
Education:		
None	10	9.3
Primary	11	10.3
Secondary	47	43.9
Tertiary	39	36.4

4.2 Overall survivorship experience

In the overall cumulative survival, 66.3% of all the patients survived their 90th days after starting dialysis and approximately 25% survived to 366 days (Table 4.2a and Figure 4.1). Their median survival time was 182 days (Table 4.2b).

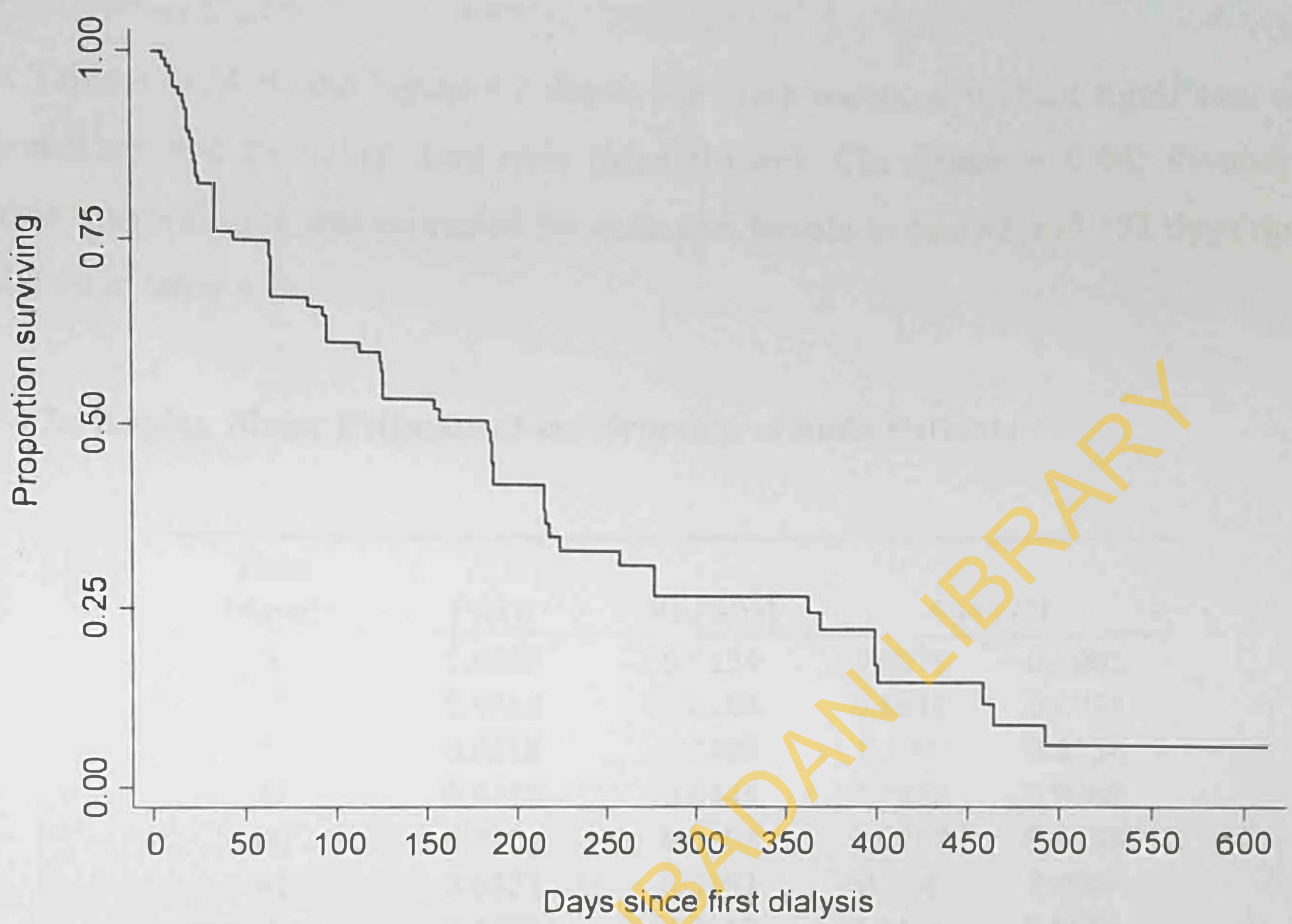
Table 4.2a Kaplan Meier Estimate of survivorship for all patients since first dialysis

Time (days)	Start total	[S(t)]	SE[S(t)]	95% CI	
5	107	0.9907	0.0093	0.9355	0.9987
15	99	0.9438	0.0223	0.8792	0.9744
21	90	0.8663	0.0333	0.7845	0.9186
31	79	0.826	0.0374	0.7379	0.8867
60	71	0.7518	0.0433	0.6547	0.8252
90	56	0.6632	0.0482	0.5593	0.748
183	34	0.4824	0.0544	0.3727	0.5836
206	25	0.4239	0.0551	0.3152	0.5284
216	20	0.3524	0.0562	0.2447	0.4617
222	19	0.3338	0.0562	0.2271	0.444
275	15	0.2712	0.0561	0.1686	0.3844
360	12	0.2486	0.0558	0.1482	0.3626
366	11	0.2486	0.0558	0.1482	0.3626
367	10	0.2238	0.0555	0.126	0.3389
397	9	0.1741	0.0531	0.0853	0.2889
399	7	0.1492	0.051	0.0668	0.2625
428	6	0.1492	0.051	0.0668	0.2625
457	5	0.1193	0.0488	0.0451	0.2326
463	4	0.0895	0.0448	0.0267	0.2004
491	3	0.0597	0.0385	0.0121	0.1654
517	2	0.0597	0.0385	0.0121	0.1654
611	1	0.0597	0.0385	0.0121	0.1654

Table 4.2b Median survival time for all patients since first dialysis

	Number of subjects	Median time (days)	Standard Error (S.E)
Overall	107	182	21.86815

Figure 4.1 Survival curves of all patients since first dialysis



4.3 Kaplan-Meier Rate of Survival according to selected characteristics and Log rank or Wilcoxon Test

1) **Sex:** Table 4.3a, 4.3b and Figure 4.2 shows that there was no statistical significant association between sex and mortality. Log rank (Mantel-Cox): Chi-square = 0.06; P-value = 0. 80. Median survival time was estimated for male and female to be 182 and 152 days respectively as shown in table 4.3c.

Table 4.3a Kaplan Meier Estimate of survivorship of male Patients

Time (days)	[S(t)]	SE[S(t)]	95% CI	
5	0.9865	0.0134	0.9079	0.9981
15	0.9458	0.0264	0.8619	0.9793
21	0.8611	0.0408	0.757	0.9228
31	0.8319	0.0443	0.7228	0.9009
60	0.7714	0.0504	0.6537	0.8534
91	0.6423	0.0592	0.514	0.745
183	0.4779	0.0648	0.3471	0.5973
275	0.2649	0.0649	0.1486	0.3963
360	0.2384	0.0636	0.1269	0.3694
397	0.1854	0.0595	0.0865	0.3133
428	0.1589	0.0566	0.068	0.284
491	0.0636	0.0415	0.0125	0.177
517	0.0636	0.0415	0.0125	0.177
611	0.0636	0.0415	0.0125	0.177

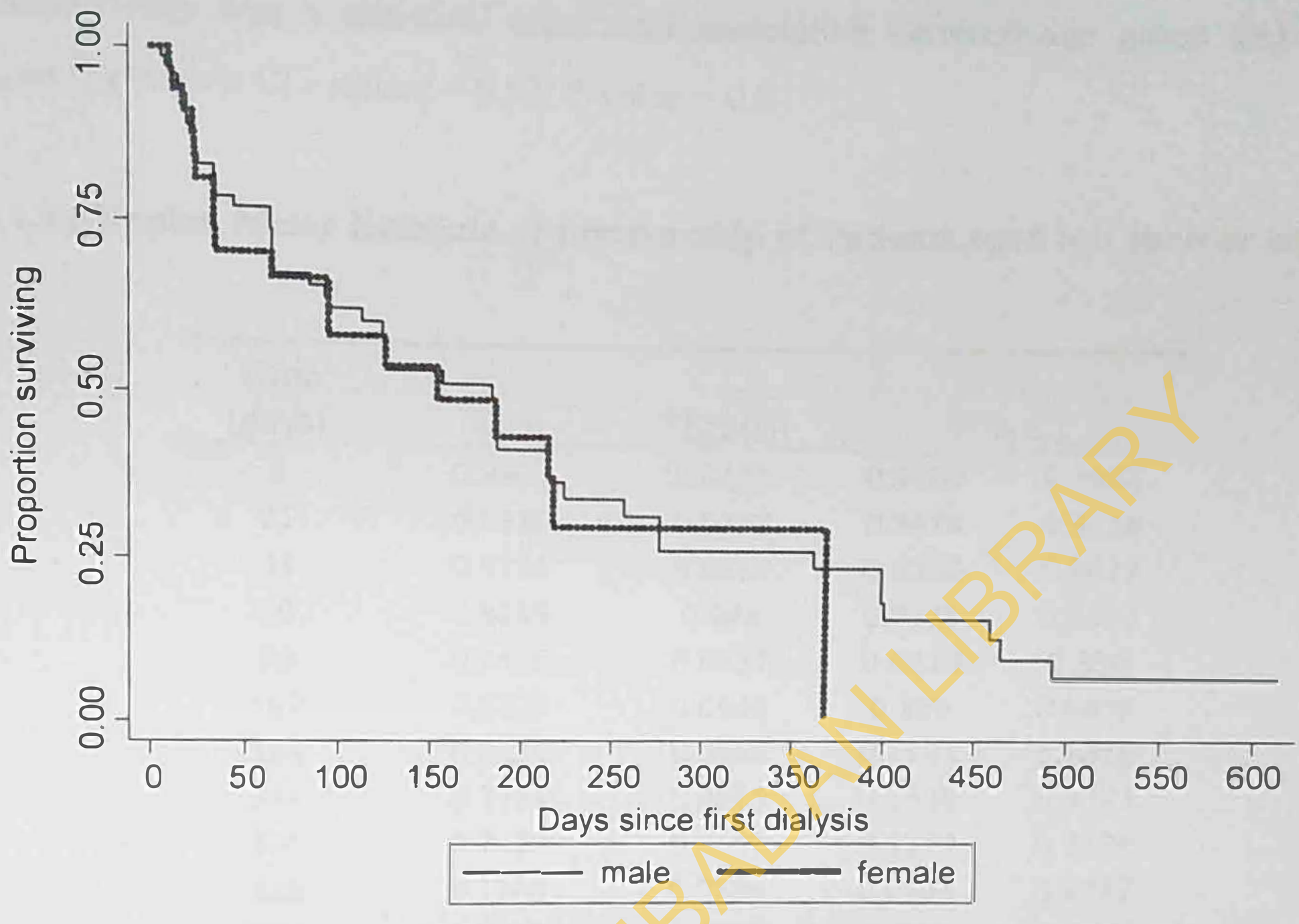
Table 4.3b Kaplan Meier Estimate of survivorship of female Patients

Time (days)	[S(t)]	SE[S(t)]	95% CI	
9	0.9697	0.0298	0.8037	0.9957
16	0.9091	0.05	0.7441	0.9697
21	0.8766	0.0578	0.7036	0.9519
29	0.8117	0.0694	0.6275	0.9108
32	0.7411	0.0793	0.5469	0.8618
63	0.6705	0.0861	0.4724	0.8081
90	0.6705	0.0861	0.4724	0.8081
93	0.5867	0.0935	0.3837	0.7432
184	0.4376	0.1024	0.237	0.6223
185	0.4376	0.1024	0.237	0.6223
366	0.3001	0.1076	0.1155	0.5111

Table 4.3c Median survival time for male and female patients

	Number of subjects	Median time (days)	Standard Error (S.E)
Male	74	182	25.95827
Female	33	152	41.41183
Total	107	182	21.86815

Figure 4.2 Survival Curves for male and female patients



2) **Age group:** Table 4.4a and 4.4b as well as Figure 4.4 show that survival (earlier survival difference) varies among the two age groups. Younger age group had a better survival experience. There was a statistical significant association between age group and mortality. Wilcoxon (Breslow): Chi-square = 6.67; P-value = 0.01

Table 4.4a Kaplan Meier Estimate of survivorship of Patients aged less than or equal to 60 years

Time (days)	[S(t)]	SE[S(t)]	95% CI	
5	0.9868	0.0131	0.9103	0.9981
21	0.9335	0.0288	0.8474	0.9718
31	0.9191	0.0317	0.8286	0.9629
60	0.8256	0.046	0.7125	0.8973
90	0.7456	0.0537	0.6219	0.834
182	0.5329	0.0648	0.399	0.6498
184	0.5132	0.0653	0.3793	0.6319
275	0.2733	0.0665	0.1536	0.4073
366	0.2429	0.0657	0.1278	0.3779
428	0.1388	0.0589	0.0493	0.2737
457	0.0925	0.0545	0.021	0.231
463	0.0463	0.0426	0.004	0.1811

Table 4.4b Kaplan Meier Estimate of survivorship of Patients aged greater than 60 years

Time (days)	[S(t)]	SE[S(t)]	95% CI	
7	0.9677	0.0317	0.7923	0.9954
21	0.7097	0.0815	0.5162	0.8371
32	0.5806	0.0886	0.3896	0.7309
62	0.5484	0.0894	0.3597	0.7026
183	0.3666	0.0982	0.1839	0.5518
184	0.3055	0.099	0.1318	0.4996
186	0.3055	0.099	0.1318	0.4996
214	0.3055	0.099	0.1318	0.4996
397	0.2037	0.1062	0.0486	0.4329
611	0.2037	0.1062	0.0486	0.4329

Table 4.4c Median survival time for less or equal 60 years and age greater than 60 years

	Number of subjects	Median time (days)	Standard Error (S.E)
Age </=60 years	76	185	30.46183
Age >60 years	31	63	54.8736
Total	107	182	21.86815

Figure 4.3 Survival curves for age group ≤ 60 years versus age group > 60 years

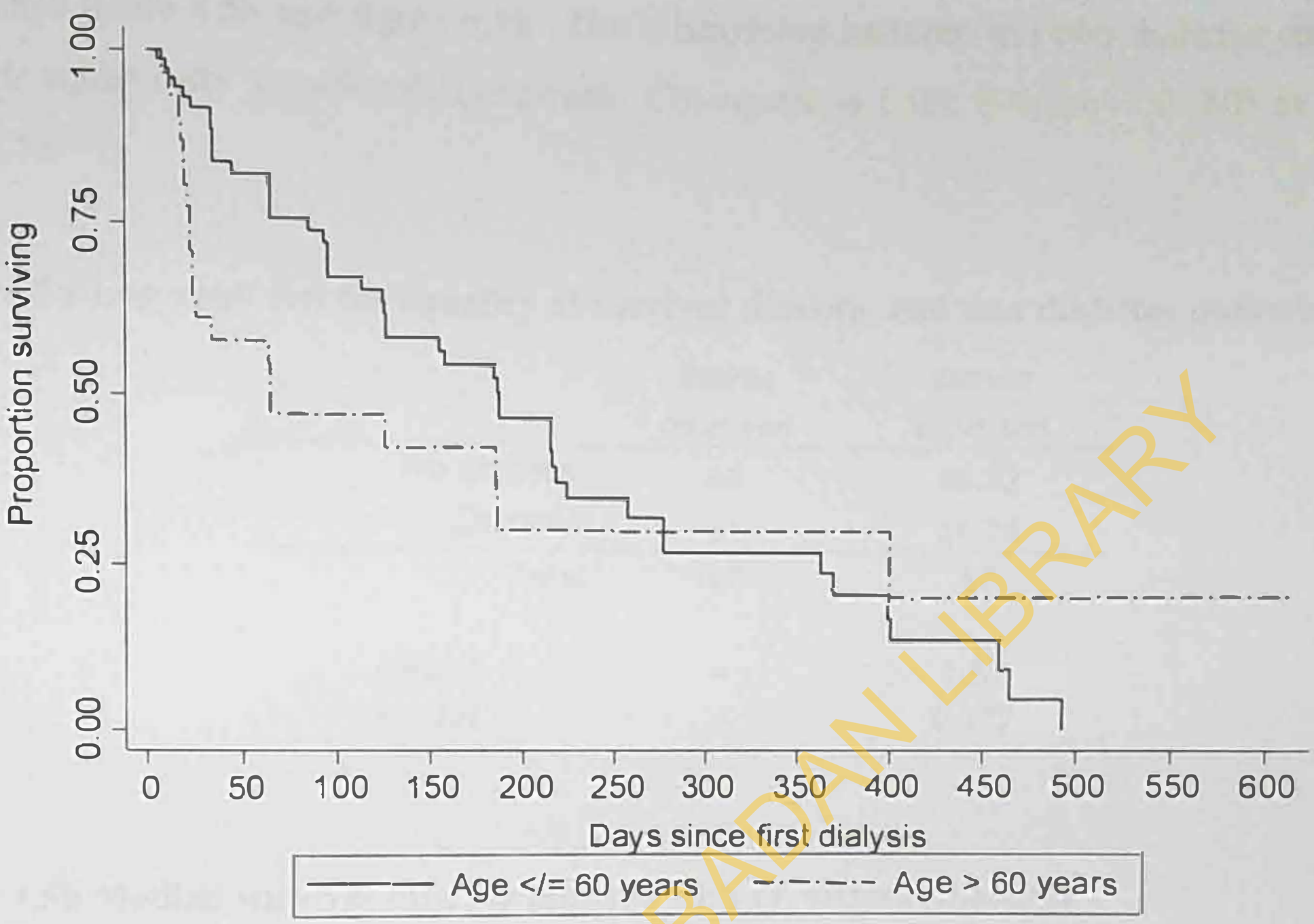
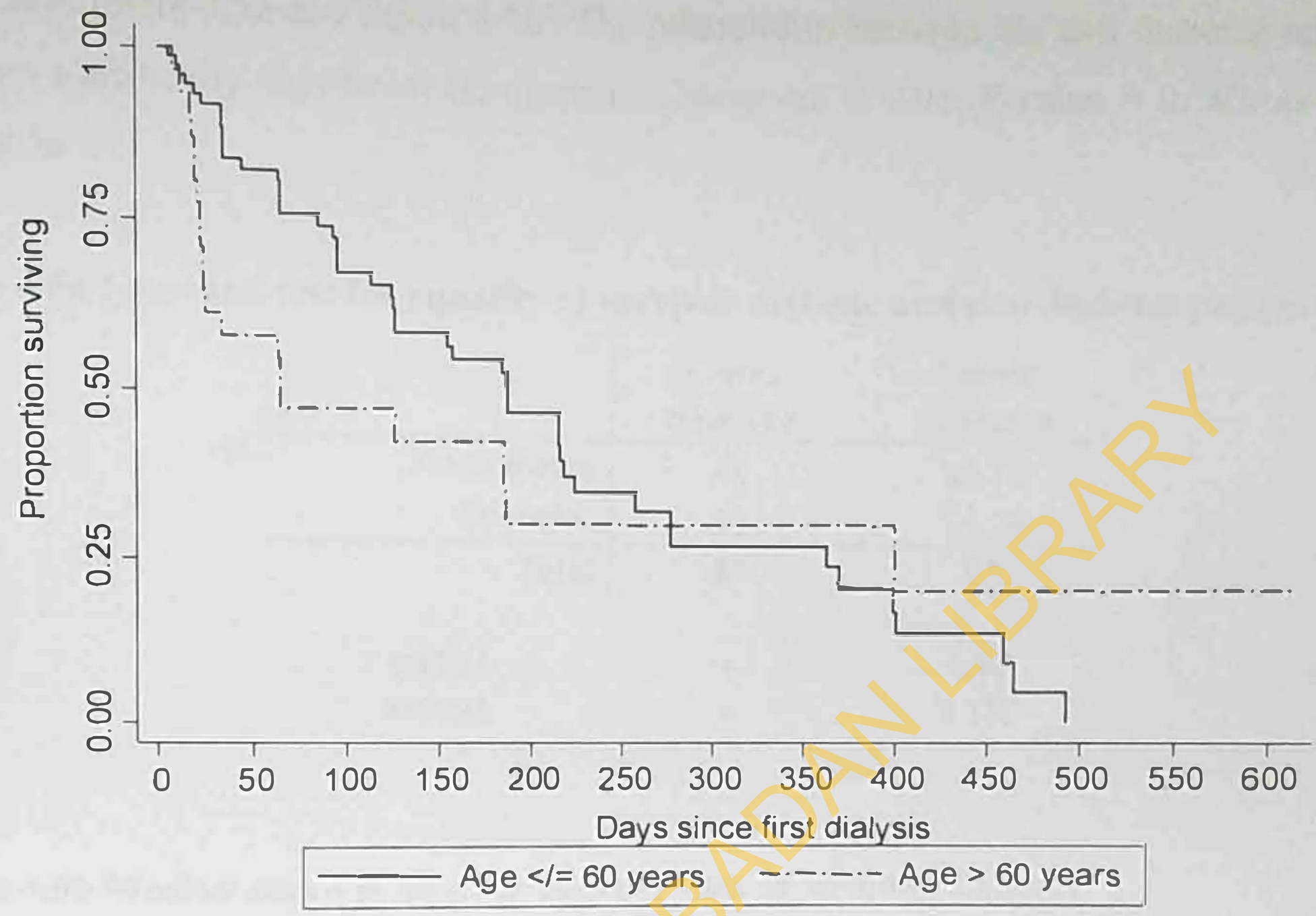


Figure 4.3 Survival curves for age group ≤ 60 years versus age group > 60 years



3) **Diabetes status:**

Median survival time for CKD patients with no diabetes is 183 days while patients with diabetes is 93 days (table 4.5b and figure 4.4). The relationship between the two diabetes status group was not statistically significant (Long-rank: Chi-square is 0.06, P-value = 0. 80) as shown in table 4.5a.

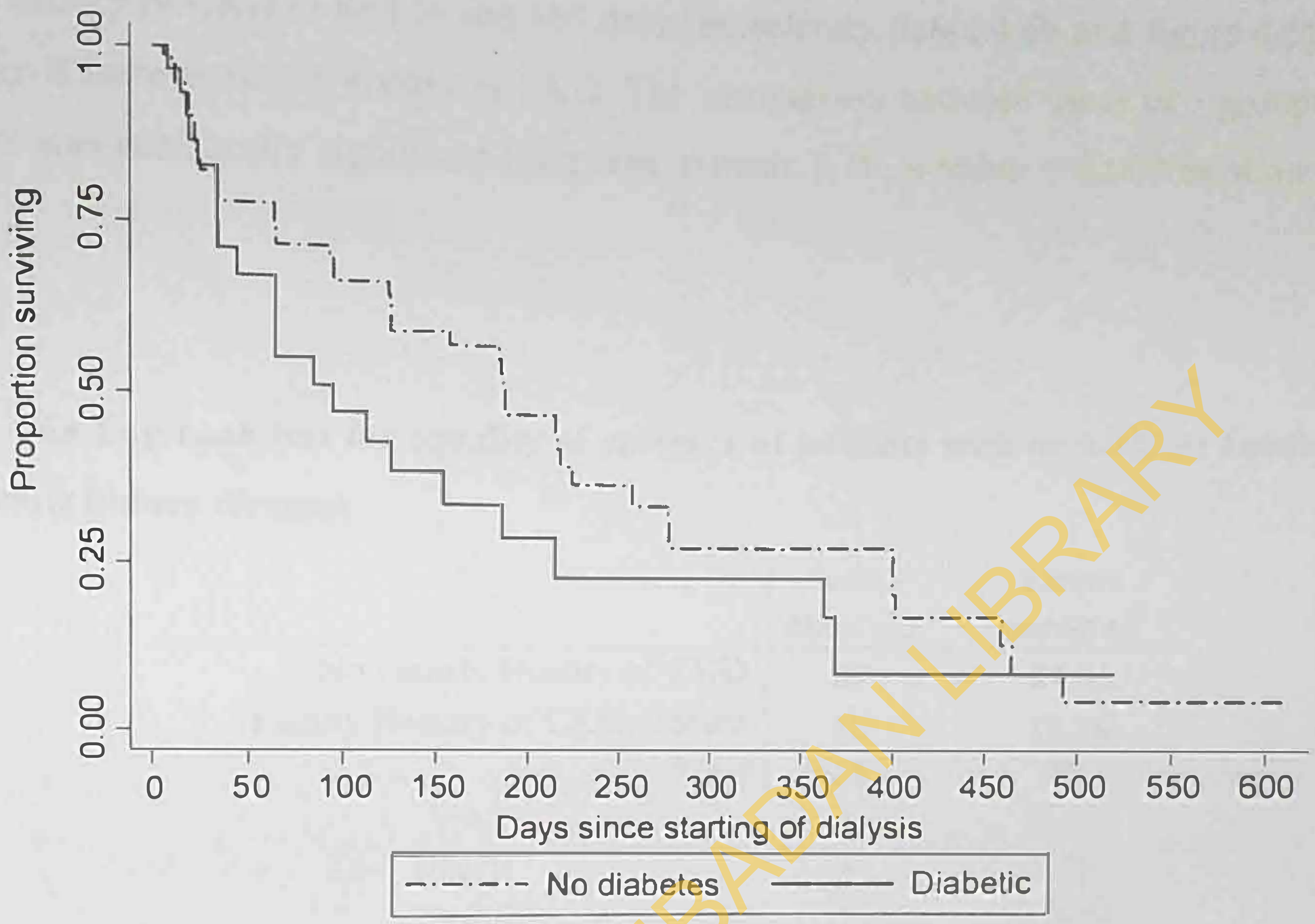
Table 4.5a Log-rank test for equality of survivor diabetic and non diabetes patients

	Events observed	Events expected
No diabetes	46	50.72
Diabetic	21	16.28
Total	67	67
chi2(1)	=	1.87
Pr>chi2	=	0.172

Table 4.5b Median survival time for patients with or without diabetes

	Number of subjects	Median time (days)	Standard Error (S.E)
No diabetes	76	185	19.04811
Diabetic	31	93	38.45375
Total	107	182	21.86815

Figure 4.4 Survival curves by diabetes status



4) Family history of chronic kidney diseases (CKD)

Median survival time was estimated for patients with no family history of CKD and patients with family history of CKD to be 124 and 367 days respectively (table 4.6b and figure 4.5). Survival is better if there is family history of CKD. The comparison between these two groups of CKD patients was statistically significant (Log rank statistic 6.78, p-value = 0.009 as shown in table 4.6a).

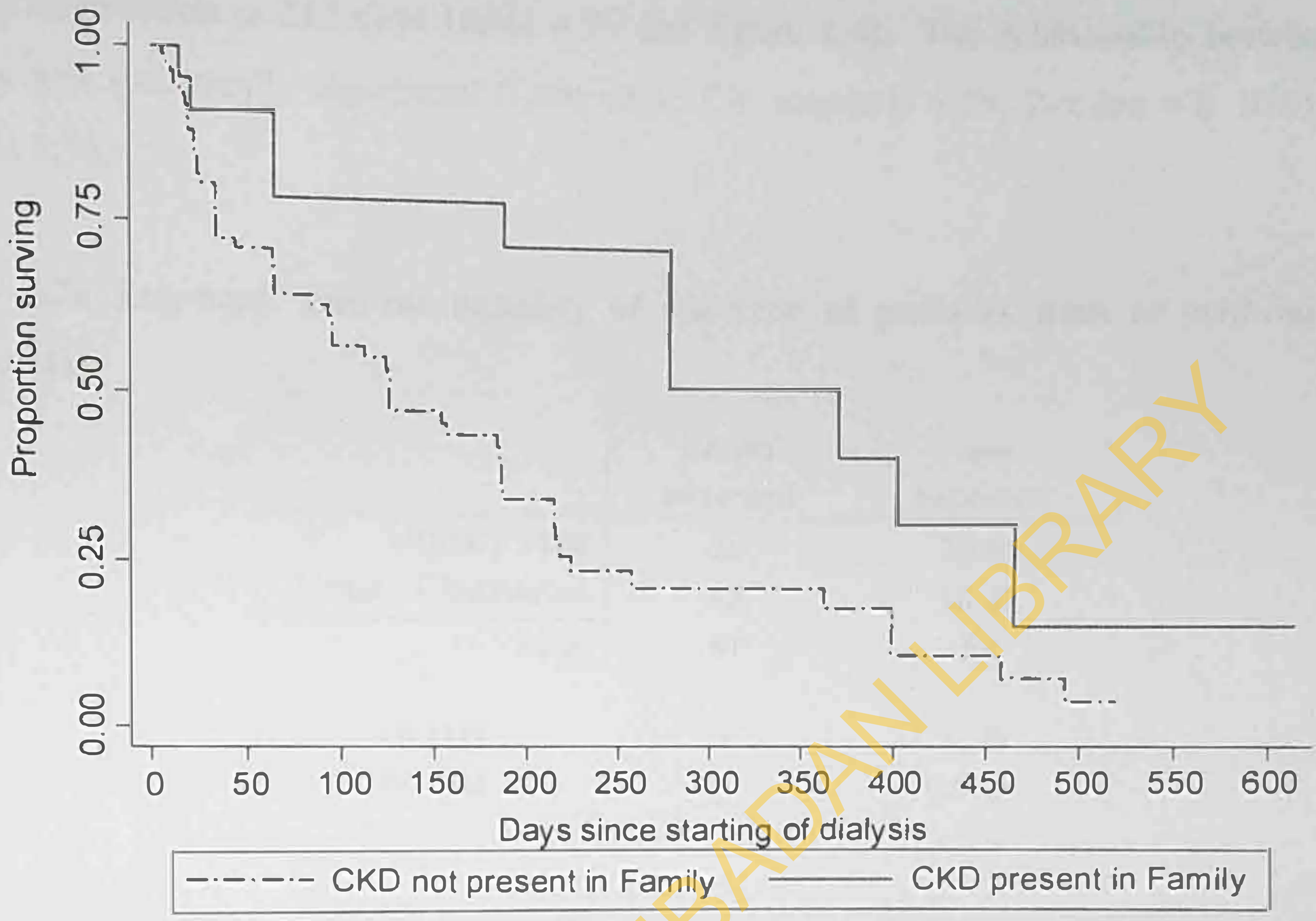
Table 4.6a Log-rank test for equality of survivor of patients with or without family history of chronic kidney diseases

	Events observed	Events expected
No Family History of CKD	57	47.64
Family History of CKD present	10	19.36
Total	67	67
chi2(1)	=	6.78
Pr>chi2	=	0.0092

Table 4.6b Median survival time for patients with or without family history of chronic kidney diseases

	Number of subjects	Median time (days)	Standard Error (S.E)
CKD history not in family	85	124	22.99521
CKD history in family	22	367	73.41747
Total	107	182	21.86815

Figure 4.5 Survival curves by family history of chronic kidney disease patients



5) **Urinary obstruction status**

Median survival time for patients with no urinary obstruction is 83 days while a patient with urinary obstruction is 213 days (table 4.5b and figure 4.4). The relationship between the two urinary was statistically significant (Long-rank: Chi-square is 5.79, P-value = 0. 016) as shown in table 4.5a.

Table 4.7a Log-rank test for equality of survivor of patients with or without urinary obstruction

	Events observed	Events expected
Urinary Free	25	16.69
Umary Obstructed	42	50.31
Total	67	67
chi2(1)	=	5.79
Pr>chi2	=	0.0161

Table 4.7b Median survival time for patients with or without urinary obstruction

	Number of subjects	Median time (days)	Standard Error (S.E)
Urinary not obstructed	40	83	37.1694
Urinary obstructed	67	213	16.50658
Total	107	182	21.86815

Figure 4.6 Survival curves by urinary obstruction status

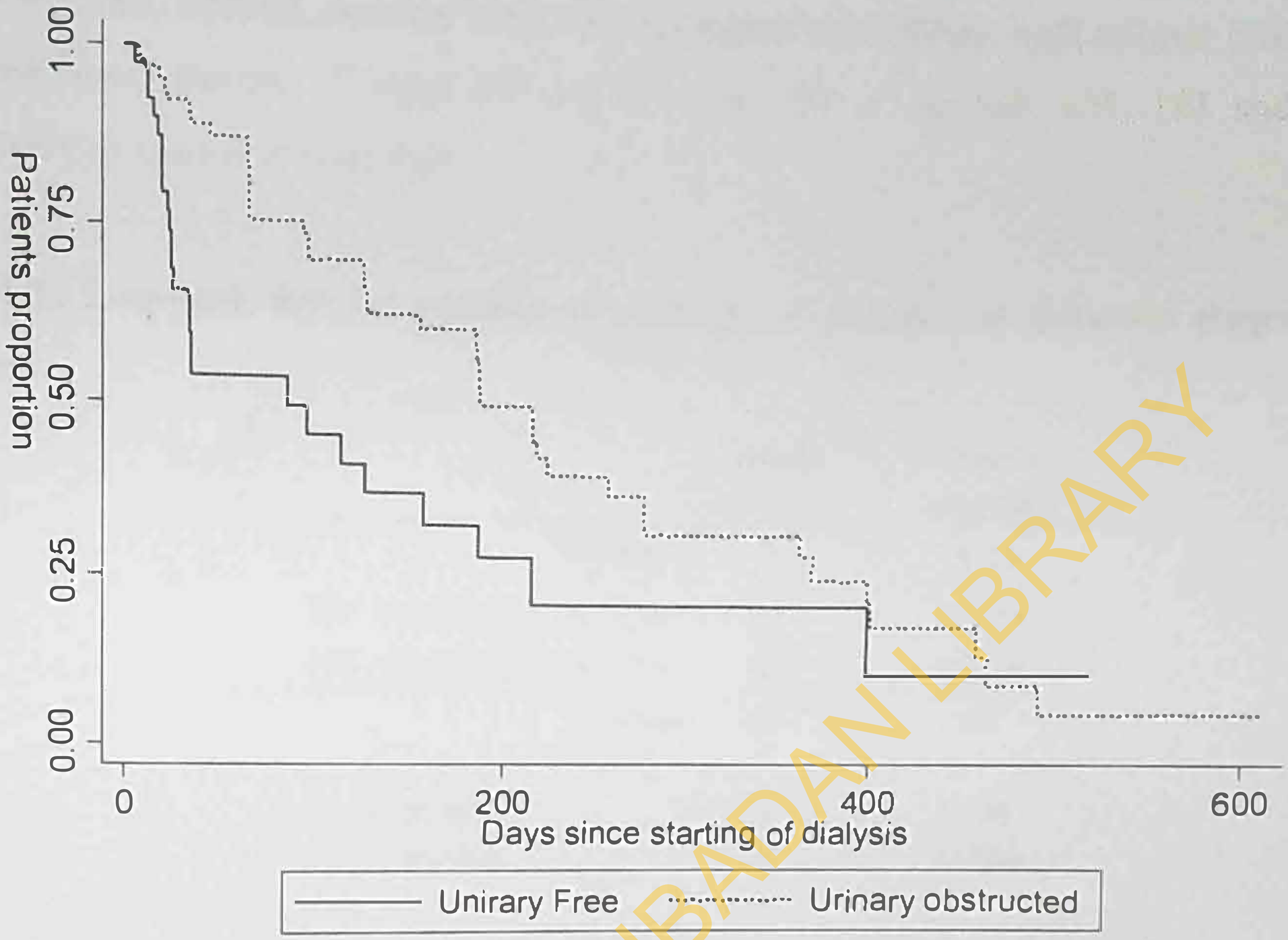
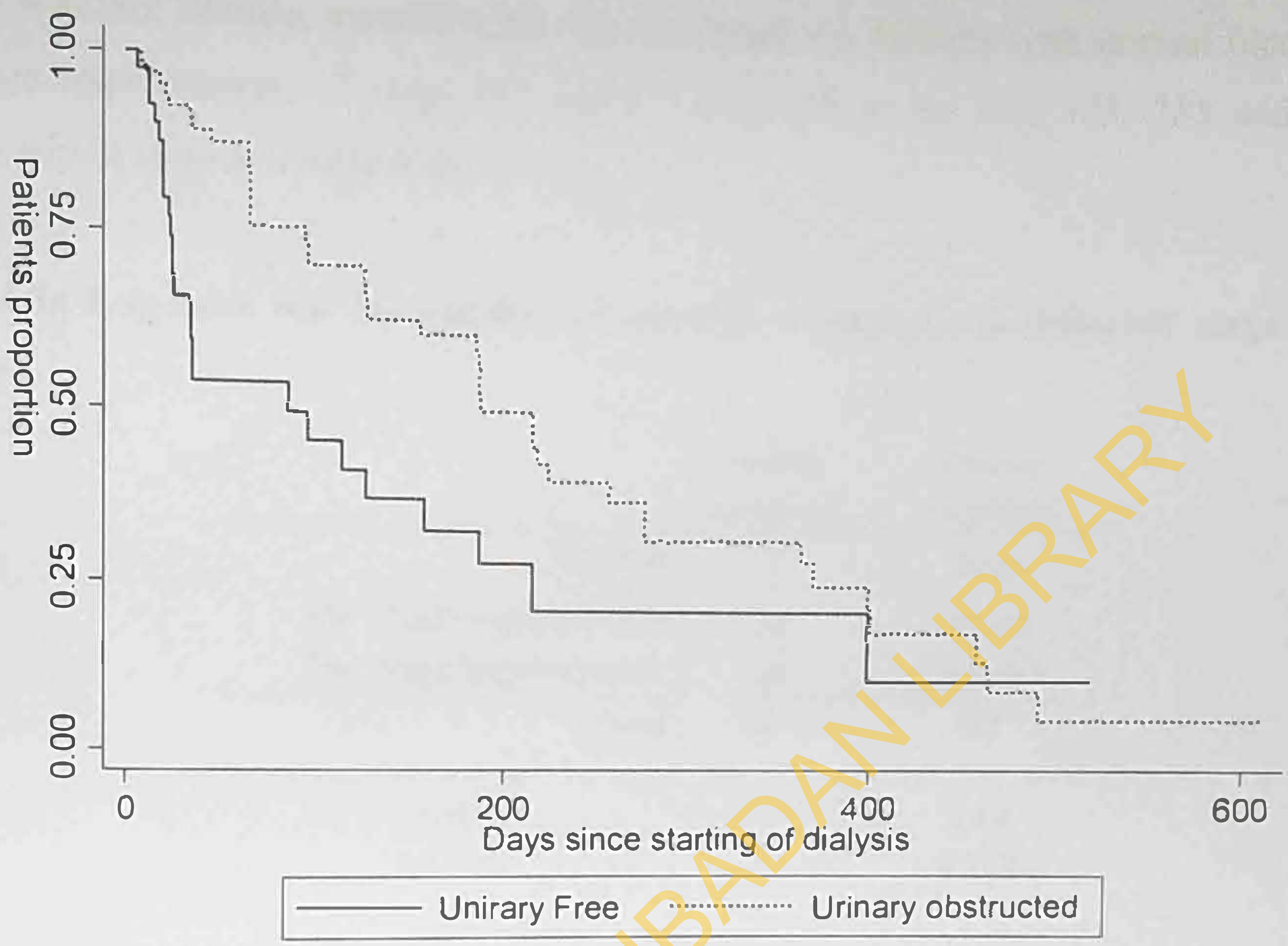


Figure 4.6 Survival curves by urinary obstruction status



6) **Blood pressure at commencement of dialysis:**

Estimation in table 4.8a and figure 4.7 shows that Log rank (Mantel-Cox): Chi-square = 0.836; P-value = 0. 80. Median survival time was estimated for patients with normal blood pressure (BP), pre hypertension, 1st stage BP and 2nd stage BP to be 360, 155, 183 and 124 days respectively as shown in table 4.8b.

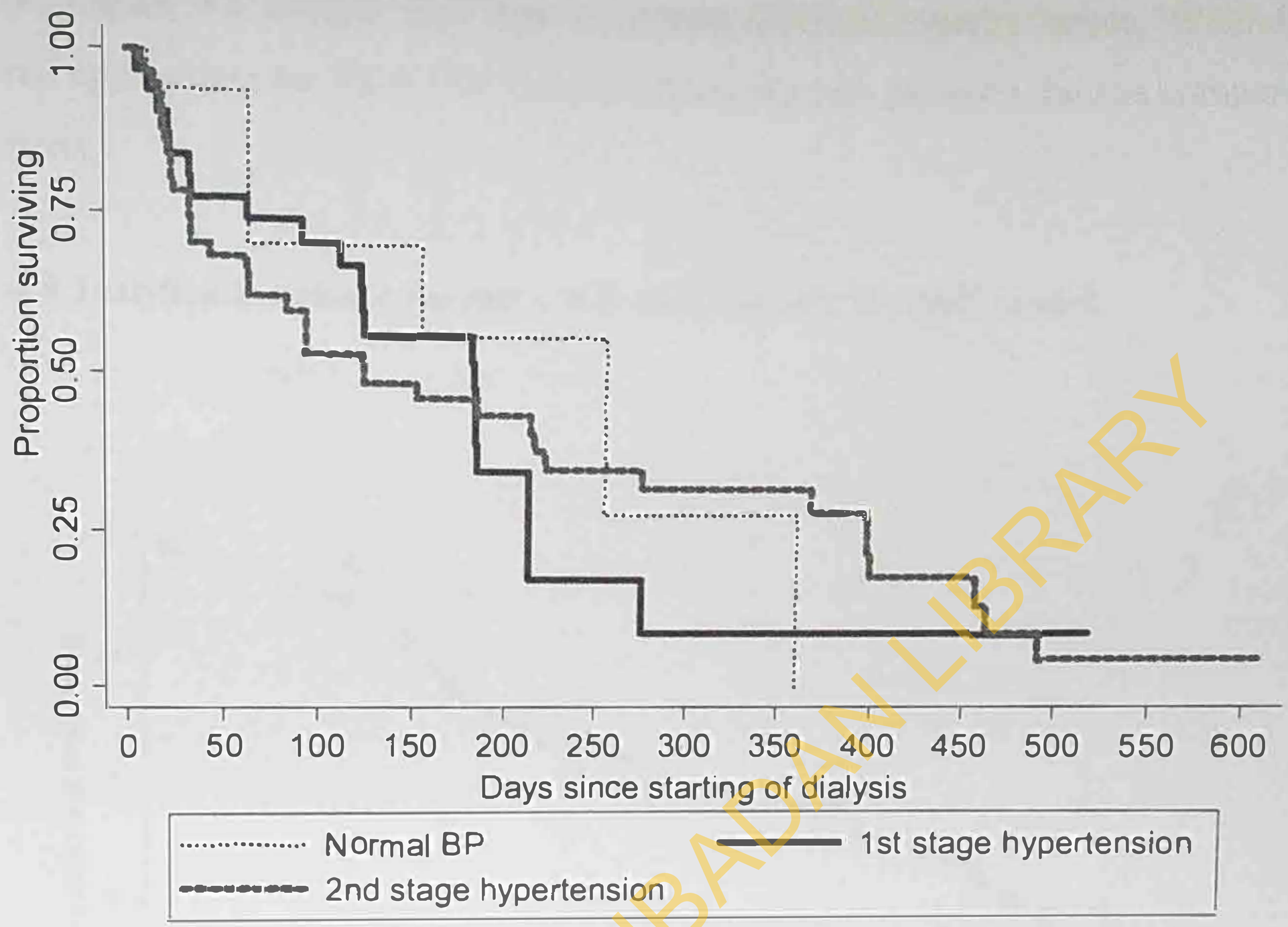
Table 4.8a Log-rank test for equality of survivor of patients in different stages of blood pressure

	Events observed	Events expected
Normal	7	9.13
1st stage hypertension	21	19.24
2nd stage hypertension	39	38.63
Total	67	67
chi2(1)	=	0.68
Pr>chi2	=	0.710

Table 4.8b Median survival time of chronic kidney diseases patients according to their blood pressure

	Number of subjects	Median time (days)	Standard Error (S.E)
Normal	17	255	7.6253
1st stage hypertension	37	183	18.48939
2nd stage hypertension	58	124	45.33949
Total	107	182	21.86815

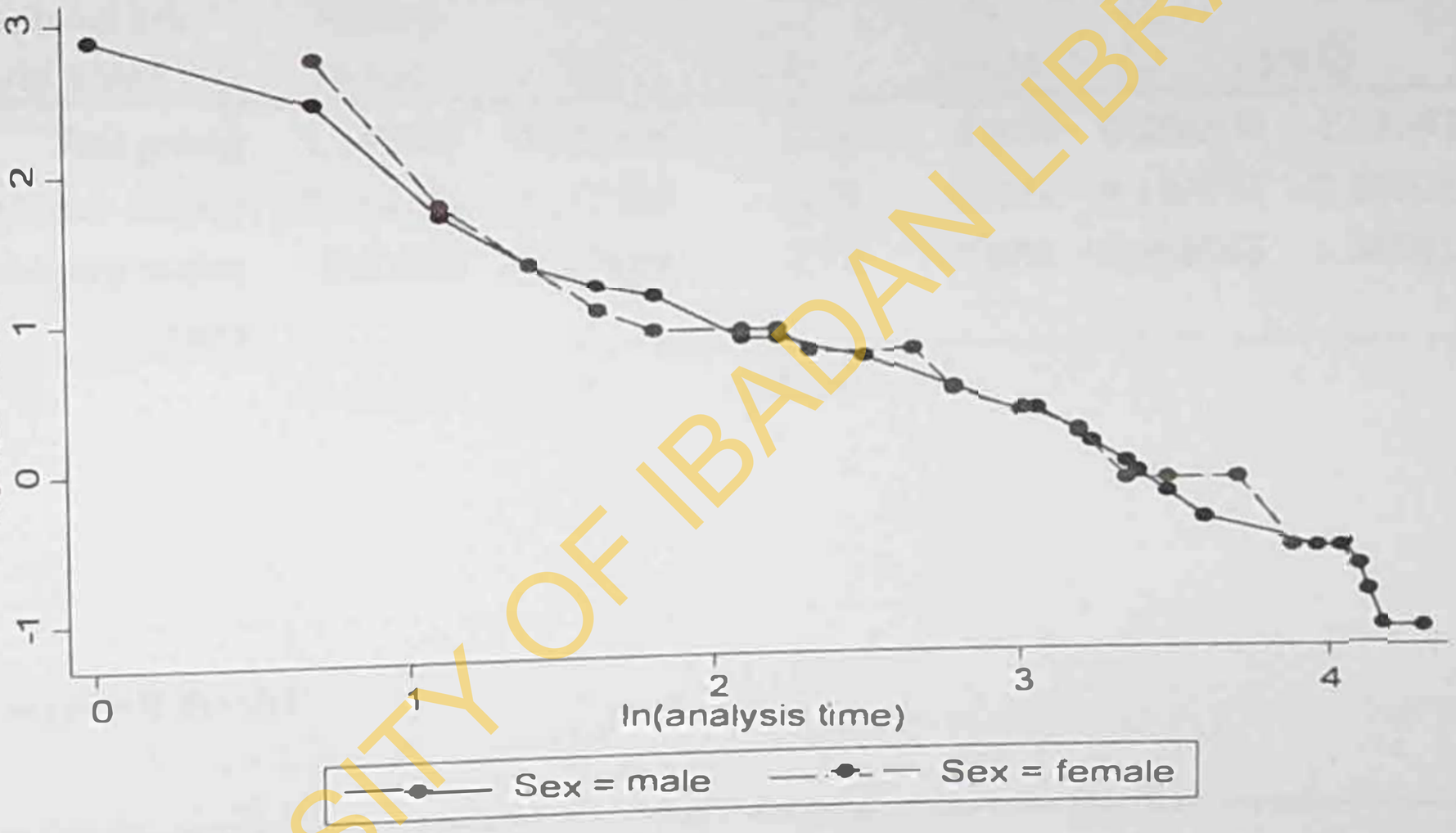
Figure 4.7 Survival curves of patients in different stages of blood pressure



4.4 Justification that collected CKD data follows Weibull distribution

A straight (approximately) line in the plot of Log {-log S(t)} versus Log (t) indicates a Weibull model. In Figure 4.8 Gender and Age covariates showed linearity hence, Weibull model is considered appropriate for EKSUTH chronic kidney disease patient's data as compared to other distributions.

Figure 4.8 Justification that collected CKD data follows Weibull model



4.5 Cox Proportional Hazard and Weibull models

The consideration of only three variables here was as a result of their statistical significances among the initial six covariates. Under the Cox Proportional Hazard model (Table 4.9) therefore, only Family history of CKD is statistically significant among others (Age group and Urinary status). Computation from Weibull model (Table 4.10) on the other hands, confirmed Family history of CKD and Urinary status to be statistically significant.

Table 4.9 Cox proportional Hazard model

Explanatory Variables	Hazard Ratio	S.E.	Z	P-values	95% CI	
Age group	1.146831	0.328604	0.48	0.633	0.654038	2.010926
F.history of CKD	0.450776	0.157754	-2.28	0.023	0.227025	0.895051
Urinary status	0.62633	0.169884	-1.72	0.085	0.368066	1.065814
_cons						
Log likelihood = -246.18						

Table 4.10 Weibull model

Explanatory Variables	Hazard Ratio	S.E.	Z	P-values	95% CI	
Age group	1.181071	0.331647	0.59	0.553	0.681172	2.047836
F.history of CKD	0.456093	0.158785	-2.25	0.024	0.230523	0.902385
Urinary status	0.585528	0.157515	-1.99	0.047	0.345592	0.992046
_cons	0.005763	0.003747	-7.93	0	0.001612	0.02061
Log likelihood = 133.811						

4.5 Cox Proportional Hazard and Weibull models

The consideration of only three variables here was as a result of their statistical significances among the initial six covariates. Under the Cox Proportional Hazard model (Table 4.9) therefore, only Family history of CKD is statistically significant among others (Age group and Urinary status). Computation from Weibull model (Table 4.10) on the other hands, confirmed Family history of CKD and Urinary status to be statistically significant.

Table 4.9 Cox proportional Hazard model

Explanatory Variables	Hazard Ratio	S.E.	Z	P-values	95% CI	
Age group	1.146831	0.328604	0.48	0.633	0.654038	2.010926
F.history of CKD	0.450776	0.157754	-2.28	0.023	0.227025	0.895051
Urinary status	0.62633	0.169884	-1.72	0.085	0.368066	1.065814
_cons						
Log likelihood = -246.18						

Table 4.10 Weibull model

Explanatory Variables	Hazard Ratio	S.E.	Z	P-values	95% CI	
Age group	1.181071	0.331647	0.59	0.553	0.681172	2.047836
F.history of CKD	0.456093	0.158785	-2.25	0.024	0.230523	0.902385
Urinary status	0.585528	0.157515	-1.99	0.047	0.345592	0.992046
_cons	0.005763	0.003747	-7.93	0	0.001612	0.02061
Log likelihood = 133.811						

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4.6 Comparison of the result form the Cox and the Weibull model

The comparison of both the Cox proportional hazard and the Weibull model as shown in table 4.11 (as extracted from table 9 and table 10), gives different results. However, the Weibull model is supported by Akaike Information Criterion with its having the smallest AIC value.

Hence, computation of hazard ratio from Weibull model imply 0.45; 95% CI 0.23 – 0.90 for Family with CKD history, taking the family with no history of CKD as the reference category. Also for Urinary status, hazard ratio from Weibull model imply 0.59; 95% CI 0.35 – 0.99 for patients with Urinary obstruction, taking patients with no Urinary obstruction as the reference category.

Table 4.11 Comparison of the result form the Cox and the Weibull model

Covariate		Cox Model HR (95% Conf. Interval)	Weibull Model HR (95% Conf. Interval)
Age Class	≤60 years (ref.) >60 years	1.15 [0.65 - 2.01]	1.18 [0.68 - 2.05]
Family history of CKD	Not present (ref.) Present	0.45 [0.23 - 0.90]	0.46 [0.23 - 0.90]
Urinary status	Not obstructed (ref.) Obstructed	0.63 [0.37 - 1.07]	0.59 [0.35 - 0.99]
Akaike Information Criterion		496.36	267.62

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4.7 Model fitting

Family history of CKD and Urinary status are the only covariates vis-a-vis others (table 4.11) that their influence on the survival chance of CKD patients that are on dialysis at EKSUTH have been confirmed. The hazard ratios of the two covariates are supportive.

Therefore, better model using computations in table 4.12 imply;

$$\mathbf{h_i(t) = -5.1499 \exp \{- 0.7850 Family\ His.\ Of\ CKD_i - 0.5353 Urinary\ status_i\}}$$

Table 4.12 Model fitting

Covariate	HR	β
Urinary status	0.5855	-0.5352891
Family his. Of CKD	0.4561	-0.7850432
Constant	0.0058	-5.14989736

CHAPTER FIVE

DISCUSSION

5.1 Discussion

Chronic kidney disease affect mainly young adults age 30 to 59. This has always been the sufferer's pattern in Sub-Saharan Africa – (Saraladevi, 2013). The overall median time was 182 days. Overall cumulative survival was 66.3% for all the patients that survived their 90th days from starting of dialysis and approximately 25% survived to 366 days. This is better than the 90th days of Ethiopia 61.5% (Tamiru 2013) and Ghana 45% (Eghan and Nsiah, 2009) in sub-Saharan Africa. These mentioned Dialysis Patients survival rates in Sub-Saharan Africa (SSA) are all lower compared to developed countries where their 2-, 5- and 10 years survival was 67, 35 and 11% respectively – (Van-Dijk and Jager, 2001).

Patients with family history of CKD are 0.46 times as likely to be at the risk of death compared to those that has no family history of CKD. This is contrary to a finding that nearly 24% of end-stage renal disease (ESRD) patients have an affiliated first degree relative, an association that is much stronger in African American than white (Henryford,2011). Similarly, Patients with Urinary obstruction at starting dialysis are 0.59 times as likely to be at the risk of death compared to those that has free Urinary. This is contrary to the findings that Urinary abnormalities, uncontrolled HTN, or metabolic abnormalities are risk factors for CKD patients (LE Boulware, et al. 2006 and TD DuBose, et al. 2009).

Other examined covariates like diabetes, blood pressure, sex and age group was confirmed to have no effects on the survival chances of CKD patients on dialysis except Age group when separately investigated.

The influences of family history of CKD and urinary obstruction are both supportive which may be explained, that the awareness of chronic kidney disease among members of family will enable other members to take to preventive measures as they are now better informed. Such individual are at advantage in avoiding late presentation and non-compliance with instructions, medications and regular dialysis. It is also likely that as part of treatment urinary obstruction would have been relieved almost immediately dialysis started. And urinary obstruction could be the underlying cause of the kidney disease.

Ekiti State University Teaching Hospital CKD patient data followed Weibull regression model, being the one with the least AIC value when compared with the Cox model which indicates the best model for registered chronic disease patients in the institution. Cox regression model with highest AIC was considered to be comparatively less efficient. This result agreed with the results obtained by Hui (2011) where comparison of Cox and Weibull model was done using gastric cancer data. These data supported Weibull model as being better.

5.2 Conclusion

Survival rate of chronic kidney disease (CKD) patients in Ekiti State University Teaching Hospital (EKSUTH) was better than those reported in others sub-Saharan Africa, but lower than the rate from developed countries. Out of the entire explanatory variables investigated for their influence on survival chances during dialysis, only family history of chronic kidney disease and urinary status were statistically significant among variables considered. Though, Age-group of patients at start of dialysis was also statistically significant when separately investigated. This study hence recommends appropriate attention to be paid to those with no family history of CKD and urinary obstruction at start of dialysis while evaluating patient for CKD.

5.3 Recommendation

1) Public awareness regards bringing people consciousness towards life style that will discourage having chronic kidney disease due to its poor surviving chances.
2) Improve interventions is needed for handling CKD patients care both by physicians and the government.
3) The model obtained in this study can be used to predict the survival chance of CKD patients obtaining dialysis in Hemodialysis Centre of Ekiti State University Teaching
4) Hospital.
5) Nigeria geo-political zone or national research on survival of CKD patients on dialysis is recommended, the study will enable the securing of larger sample size.

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