



# Statistical Modelling of Staff Survival Time in Service at Chuka University

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## Authors' contributions

*This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.*

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## Abstract

Staff attrition is identified as a major challenge affecting the education sector globally and in Kenya. The main objective of this study is to develop a statistical model of staff survival time in service at Chuka University. The study investigated seven covariates (Gender, age group, Marital Status, Terms of employment, staff Category, staff Highest Qualifications and Job group) on the outcome variable which is staff survival time in Service at Chuka University. In this research, survival analysis methods that were used are the Kaplan Meier and log rank test, the Cox-proportional hazard model and the Accelerated Failure Time models (Weibull AFT Model). The cox proportional regression model was employed to study the effect of the covariates on the survival time of the staff at Chuka University. To compare the survival rate of different groups of staff, the study employed the use of Kaplan Meier Estimator. To test if a difference exists in survival time between two or more independent groups, this study applied log-rank test. The results on the Univariate Cox PH Model showed that the covariates, gender, age group, terms of employment, staff category, highest qualification and Job group were statistically significant at 5% level of significance except for the Marital status which was insignificant associated with the survival time of staff at Chuka University.

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The study was able to predict the probability of survival of staff using the covariates. The findings from the study showed that the male staff have high survival probability compared to their female counterparts: the younger employees between the age of 18-25 stay in service for fewer years compared to those between the age of 26-35 and 36-50. Further results indicated that, The Weibull AFT model give the best model fit with more precise estimates that had small standard errors compared to the Cox Proportional Hazard Model. These findings will be beneficial for the policy makers to review the policies related to staff retention at different Universities in Kenya and more especially to the Chuka University, Human Resource Management to make informed decisions and implement strategies to improve staff retention and more effective recruitment strategies. These policies include Professional Development Programs: Universities may offer ongoing training and development opportunities, such as workshops, certifications, and seminars, to help staff improve their skills and advance their careers. Also Universities can offer competitive salaries, performance- based bonuses, and comprehensive benefits packages (health insurance, retirement plans, tuition waivers) to retain staff.

*Keywords: Survival analysis; survival time; staff attrition; survival rate; hazard rate.*

## Abbreviations

*AFT* : Accelerated Failure Time  
*ANOVA* : Analysis of Variance  
*Cox PH* : Cox Proportional Hazard  
*TSC* : Teacher Service Commission

## 1 Introduction

Survival analysis is a statistical method to determine the duration until an event occurs. As the name suggests, survival analysis was devised by the biomedical sciences to analyze the percentage of patients who survived to specific points after receiving a treatment; since then, it has been used in several instances where the binary event of interest is the event occurs or it does not occur (Clark et al., 2003). Apart from the medical field, survival analysis is applied in other areas like social science, engineering, and human resource management. Survival analysis analyzes time-to-event data (Cox, 1972). It is beneficial when studying the time it takes for an event of interest, such as death, failure, recovery, exit from employment, or any other significant event (Flynn, 2012). In career, the events include death, resignation, dismissal, or retirement. In survival analysis, the duration until a particular event or end point is the main emphasis.

When carrying out Survival Analysis, important step in creating appropriate models for censored data is estimating the survivor function using the Kaplan-Meier estimator (In & Lee, 2018). While non-parametric techniques such as the Kaplan-Meier estimator perform well on homogenous data, they are unable to ascertain the relationship between particular factors and survival times (Kaplan & Meier, 1958). Because of this need to examine survival data, regression techniques are applied. In the field of survival analysis, models based on the hazard function have dominated since Cox (Kleinbaum & Klein, 2012) developed the Cox proportional hazards (PH) model. Due to its simplicity and lack of assumption on the survival time distribution, this model is widely used in survival analysis (Likoko & Barasa, n.d.). However, not every situation will lend itself to the Cox PH model. We can investigate how the given factors affect the likelihood that a specific event (such as resignation, retirement, dismissal, or death) will occur using the Cox proportional Hazard model. The term "hazard rate" refers to the frequency of a particular incident occurring.

The predictor variables (gender, Age, Salary, marital status, level of education, terms of service, and working experience) are usually termed covariates. This type of analysis works for both quantitative and categorical predictor variables. The Cox regression model extends survival analysis methods to simultaneously assess several risk factors' effects on survival time. Another method for analyzing survival data is to utilize the Accelerated Failure Time (AFT) models (Cox and Oakes, 1984; Collet, 2003). They offer models that are more reliable and accurate.

Staff attrition has become a major challenge in public universities. Factors that have led to staff attrition include limited funding and lack of career advancement. Public universities often face budget constraints, resulting in

lower salaries, fewer benefits, and limited resources (Mamuli et al., 2017). This leads to staff leaving in search of better opportunities. The limited opportunities for career advancement or professional development within a public university often cause teams to look elsewhere for opportunities to advance their careers. As the labor market has changed, open competition for other universities' staff and strategic poaching of key and skilled employees has become common.

In the twenty-first century, employee turnover has become a significant concern for HR professionals, Boards of Management (BoMs), and enterprises. The HR manager is responsible for choosing the most skilled and motivated workers for the company and for keeping them on board. Management and academia have both paid close attention to employee turnover. Smith (Mugove & Mukanzi, 2018) contended that organizations in the United States of America (USA) spend more than \$200 billion a year on hiring and personnel replacement. There are several accounts of excessive teacher turnover in affluent nations like the United States. Academic staff turnover in Britain is said to be significantly increasing. In Sweden, things are getting worse as well (Santiago & Mackenzie, 2005). A 2009 survey by the Central Bureau of Investigation revealed that the average worker turnover rate in the UK is 15.7%.

Kenya has experienced a significant brain drain over the years, with many skilled professionals and technical personnel in public universities leaving the country for other countries, especially Europe and America. The high intake rate in Kenya's public universities has led to staff attrition due to the high staff-to-student ratio. With the high rates of intake of students, employees in these universities experience heavy workloads (Mwambi, 2008). The increased information has also strained resources such as lecture rooms, laboratories, and equipment. This has made it challenging for the staff to provide quality education and research, leading to frustration and a desire to leave. Furthermore, there is a widespread internal brain drain as highly qualified employees leave these colleges for other industries within the same nation, such as private universities, where they are perceived to offer better working circumstances (Ng'ethe, 2014).

Likoko & Barasa (Schober & Vetter, 2018) researched salary satisfaction and turnover intentions among the teaching staff in public universities in Kenya. In their findings, the authors discovered that 73.4% of the academic staff disagreed with whether they were satisfied with their current payments. This is an excellent figure to show that the teaching staffs in the public universities in Kenya are not satisfied with the salaries that they receive. 63% of the population agreed they were underpaid concerning their duties, while 64.4% disagreed on whether the salary increments were regular. The study concluded that low salaries paid to the teaching staff in the public universities in Kenya are a significant factor leading to staff attrition in these institutions.

Mugove & Mukanzi (Mamuli et al., 2017) examined the determinants of employee turnover in selected Kenyan public universities (Masinde Muliro University of Engineering and Technology, Maseno University, and Kibabii University). In their findings, 36.3% of the respondents strongly agreed that they could leave their job as soon as possible, with 39.2% strongly agreeing that they always thought a lot about going to their university. On the other hand, 51.2% agreed that they were already searching for alternatives in other organizations. Furthermore, 35.8% of the respondents agreed they would probably look for new jobs elsewhere in the following years. Others decided that they would leave the institutions in the coming few years and agreed to look for jobs unrelated to the public sector. The study discovered a strong positive correlation between employee turnover and job satisfaction, implying that many employees in these universities were not satisfied with their job. Factors mainly contributing to this include heavy workload, lower salaries, and poor working conditions. The lack of salary increment policies also contributes to the high staff attrition rate in these institutions of higher learning. The aim of this study is to fit a statistical model to determine staff survival time in service at Chuka University (Smith, 2017; Mwambi, n.d.).

## **2 Methodology**

### **2.1 Data collection**

The data for this study was obtained from the Human Resource Department at Chuka University. Data on Age, gender, salary (job group), marital status, staff highest qualification, staff category and terms of Employment obtained from the Human resource records was accurate and relevant in addressing the objectives of this study. The data focused on the staff who have been in service since 2012 to 2023.

## 2.2 Survival methods

The most widely used method in survival analysis is the Kaplan-Meier estimator, which provides nonparametric survival function estimates based on observed data (Flynn, 2012). Other advanced techniques, such as Cox proportional hazards regression, were employed to assess the impact of covariates (independent variables) on survival time while controlling for confounding factors. The primary characteristics of survival analysis included the following:

### 2.2.1 Survival function

According to Aalen et al. (2008), the survival function calculates the likelihood that a person will live past a specific time point  $T$  without encountering the relevant event. The survival function is denoted as  $S(t)$ .

$$S(t) = P(T \geq t) = 1 - P(T < t) = 1 - F(t), t \geq 0 \tag{1}$$

where  $T$ - Survival time in this case the employment duration of the staff at Chuka University and  $t$ - is an arbitrary time point.

The likelihood that Chuka University employees would continue to work there for at least  $t$  years was referred to as the survival function in this study.  $T$  stood for the length of time employed. It was supposed that the survival time was a discrete random variable that only accepted positive integers. The survival estimates were calculated by applying the Kaplan-Meier method.

$$S(t) = \prod_{j=1}^k \frac{n_j - d_j}{n_j} \tag{2}$$

$n_j$  Represented the number of employees observed at the time  $t_j$  and  $d_j$  is the number of employees that exited from service.

### 2.2.2 Hazard function

If the person has survived up to that point, the hazard function shows the instantaneous rate at which the event will occur at a given time.

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P[t < T \leq t + \Delta t / T > t]}{\Delta t} = \frac{F(t + \Delta t) - F(t)}{\Delta t \cdot S(t)} = \frac{f(t)}{S(t)} \tag{3}$$

where  $f(t) = \frac{d}{d(t)} F(t)$  is the probability density function of random variable  $T$ . The hazard function can also be

written as 
$$h(t) = \frac{-d \log S(t)}{d(t)}$$

In this paper, the hazard function was employed to describe the intensity of an event occurring at a given time  $t$  given that the individual has already survived past time  $t$ .

## 2.3 Non-parametric models

### 2.3.1 Kaplan-meier estimator

The survival probability at various time points are estimated sequentially by the Kaplan-Meier estimator. The median survival time for each covariate was compared using the Kaplan-Meier curves.

Assume that Chuka University employs  $n$  staff members, each of whom has an observed survival time.  $t_1 \leq t_2 \leq \dots \leq t_n$ . Among these events, we have  $r \leq n$  distinct times. The  $r$  event times are arranged in ascending order such that.  $t_{(1)} \leq t_{(2)} \leq \dots \leq t_{(r)}$  denoting the  $j^{th}$  event or exit time as  $t_j$ .

Let the number of Chuka University staff at risk of exit just before the time.  $t_j$  be  $n_j$  and  $d_j$  the number of exit times at the time  $t_j$ . The probability of surviving through time intervals  $[t_j, t_{j+1}]$  is then  $\frac{n_j - d_j}{n_j}$ .

## 2.4 Semi-parametric models

### 2.4.1 The cox proportional model

This study used both the Univariate and Multivariate Cox PH model to measure the significance of each explanatory variable. This model assisted in selecting the variables included in the final model. The Cox proportional hazards model gives you the ability to analyze time-to-event data, such as the survival time of individuals, while taking the influence of multiple covariates into consideration (Kleinbaum & Klein, 2012).

The hazard function is given as:

$$h(t) = h_0(t) \times \exp(\beta_1x_1 + \beta_2x_2 + \dots + \beta_px_p) \tag{4}$$

Where:

$h(t)$  is the hazard function for an individual at time  $t$ .

$h_0(t)$  The baseline hazard function represents the hazard when all covariates are zero.

$\beta_1, \beta_2, \dots, \beta_p$  Are the regression coefficients associated with the covariates  $x_1, x_2, \dots, x_p$

This helped in addressing the first hypothesis that states that there is no significant effect of the selected variables on the survival time in service of Chuka University employees.

## 2.5 Parametric models

### 2.5.1 Weibull AFT model

There are times when the proportional assumption is not met in the Cox Proportional Model, in this case a parametric survival analysis model, particularly the accelerated failure time (AFT) model, is used. In this Paper the Weibull AFT model, which is believed to give a good estimate compared to the Cox PH model was employed.

The Weibull distribution with shape and scale parameters  $\alpha$  and  $\lambda$ , respectively, have the survival function;  $S_T(t) = e^{-(\lambda t)^\alpha}$  and the hazard function as;  $h_T(t) = \alpha\lambda^\alpha t^{\alpha-1}$  for all  $t \geq 0$  and  $\lambda, \alpha, > 0$ . The hazard function

increases if  $\alpha > 1$  and decreases if  $\alpha < 1$ . When  $\alpha = 1$ , the Weibull model reduces to the exponential model.

In this case, we have;

$$S_{T|x}(t|x) = \exp(-(\lambda t)^\alpha) \tag{5}$$

Where;

$$\frac{1}{\exp(\beta_0 + \beta X)} = \lambda \tag{6}$$

## 3 Results and Discussions

### Data Description and Exploratory Analysis.

The gender distribution of Chuka University staff members is shown by the data, with a higher percentage of female employees (54.24%) than male employees (45.76%). The bulk of employees (51.66%) are between the ages of 36 and 50, and a sizable percentage are married (60.52%). When it comes to employment, the majority of employees (81.67%) are on permanent contracts, and a higher proportion of them work in administrative capacities (63.84%) than in academic jobs. In terms of credentials, 25.22% of the employees have a Master's degree, while the remaining employees have a variety of credentials, from certificates to PhDs. According to the job group distribution, the lowest job group A (I–V) comprises nearly half of the workforce (45.88%), while the highest job group D (XVI–XX) has the least number of employees (0.25%).

**Table 1. Demographic and employment characteristics of staff members**

| <b>Variable</b>              | <b>Frequency</b> | <b>Percentage</b> |
|------------------------------|------------------|-------------------|
| <b>Gender</b>                |                  |                   |
| Male                         | 372              | 45.76             |
| Female                       | 441              | 54.24             |
| <b>Age Bracket</b>           |                  |                   |
| 18-25                        | 8                | 0.99              |
| 26-35                        | 182              | 22.39             |
| 36-50                        | 420              | 51.66             |
| 51-75                        | 203              | 24.96             |
| <b>Marital Status</b>        |                  |                   |
| Married                      | 492              | 60.52             |
| Separated/Divorced           | 73               | 8.98              |
| Single                       | 248              | 30.50             |
| <b>Terms of Employment</b>   |                  |                   |
| Contract                     | 149              | 18.33             |
| Permanent                    | 664              | 81.67             |
| <b>Staff Category</b>        |                  |                   |
| Academic staff               | 294              | 36.16             |
| Administrative Staff         | 519              | 63.84             |
| <b>Highest Qualification</b> |                  |                   |
| Certificate                  | 168              | 20.66             |
| Diploma                      | 123              | 15.13             |
| Undergraduate                | 161              | 19.80             |
| Masters                      | 205              | 25.22             |
| PhD                          | 156              | 19.19             |
| <b>Job Group</b>             |                  |                   |
| A (I-V)                      | 373              | 45.88             |
| B (VI-X)                     | 78               | 9.59              |
| C (XI-XV)                    | 360              | 44.28             |
| D (XVI-XX)                   | 2                | 0.25              |

### 3.1 Distribution of the survival time of staff

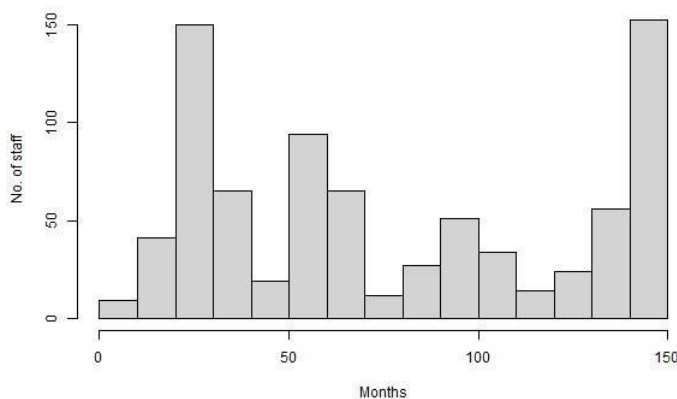
The study sought to establish the distribution of survival times in months of staff at Chuka University. The results are shown in Fig. 1.

Results in the figure above displays the number of staff over different months. There is steady increase in the number of staff in the initial months and peaking around the 20<sup>th</sup> month before a sharp decrease in staff numbers implying a significant decline. The trend is repeated after 50<sup>th</sup> month where the number kept increasing and decreasing.

### 3.2 The survival function and results

The survival rates among Chuka University staff as shown in Table 2 above show variation across different groups. Males (0.7710) have a higher survival rate compared to females (0.6747). This is because most female staff face more challenges in balancing work and family responsibilities, leading to higher exit rates. This includes maternity leave, childcare, and other family-related obligations that might not affect male staff to the same extent. In terms of age, staff aged 36-50 have the highest survival rate (0.8095), while the 18-25 age group has the lowest (0.375). This is because, staff in 18-25 age group typically consists of younger staff who are early in their careers who face more job instability and higher turnover rates as they seek better opportunities or adjust to the demands of a new professional environment. Staff in this age bracket 51-75 are closer to retirement age. Health issues, retirement, or voluntary exit from the workforce contribute to lower survival rates. While on the other hand, staff in age groups 26-35 and 36-50 are often more established in their careers, benefiting from greater job security and professional development opportunities. Staff who are single (0.7419) or separated/divorced (0.7260) show slightly higher survival rates compared to married staff (0.7195). Permanent employees (0.8720) have significantly higher survival rates than those on contract (0.0805). This is because

permanently employed staff enjoy greater job security, which lead to increased job satisfaction, stability, and lower turnover rates. This stability therefore contributes to a higher survival rate within the organization. On the other hand, Contractual employment often involves job insecurity, with contracts potentially being temporary or subject to renewal. This uncertainty led to higher turnover rates and lower overall survival times within the organization. Academic staff (0.7857) fare better than administrative staff (0.6936). Staff with PhDs (0.8323) have the highest survival rates by qualification, followed by master's holders (0.8012), while those with certificates have the lowest (0.4702). The reason behind this is that the certificate holders experience lower job satisfaction due to limited responsibilities, lower pay, and fewer professional development opportunities, leading to higher turnover rates. Diploma and Undergraduate Degree Holders, Experience moderate job satisfaction but may still aspire for higher qualifications or more fulfilling roles, affecting their tenure. While those with Masters and PhD experience higher job satisfaction due to more complex and rewarding job responsibilities, better pay, and greater recognition within the academic community. This satisfaction contributes to higher survival rates. In job groups, Group C (XI-XV) has the highest survival rate (0.7805), while Group D (XVI-XX) has the lowest (0.5), though this is based on only two individuals.



**Fig. 1. The distribution of the survival time of staff**

### 3.3 The univariate cox PH model

$H_0$ : There is no significant relationship between the covariates and the survival time of the staff

After carrying the Univariate Cox PH model, the results showed that the p values associated with the variables gender, age, Terms of employment, staff category, highest qualification and Job group are less than 0.05 indicating that these variables (Covariates) are statistically significantly associated with the survival time of staff in service. On the other hand, the p value associated with marital status of the staff is less than 0.05 which shows statistically insignificant relationship between the marital status of the and their survival time overtime.

**Table 2. Events and survival rates by the covariates**

| Factor                | N   | Events | Survival Rates |
|-----------------------|-----|--------|----------------|
| <b>Gender</b>         |     |        |                |
| Female                | 372 | 121    | 0.6747         |
| Male                  | 441 | 101    | 0.7710         |
| <b>Age Bracket</b>    |     |        |                |
| 18-25                 | 8   | 5      | 0.375          |
| 26-35                 | 182 | 54     | 0.7033         |
| 36-50                 | 420 | 80     | 0.8095         |
| 51-75                 | 203 | 83     | 0.5911         |
| <b>Marital Status</b> |     |        |                |
| Married               | 492 | 138    | 0.7195         |
| Separated/Divorced    | 73  | 20     | 0.7260         |
| Single                | 248 | 64     | 0.7419         |

| Factor                       | N   | Events | Survival Rates |
|------------------------------|-----|--------|----------------|
| <b>Terms of Employment</b>   |     |        |                |
| Contract                     | 149 | 137    | 0.0805         |
| Permanent                    | 664 | 85     | 0.8720         |
| <b>Staff Category</b>        |     |        |                |
| Academic Staff               | 294 | 63     | 0.7857         |
| Administrative Staff         | 519 | 159    | 0.6936         |
| <b>Highest Qualification</b> |     |        |                |
| Certificate                  | 168 | 89     | 0.4702         |
| Diploma                      | 123 | 30     | 0.7561         |
| Undergraduate                | 205 | 45     | 0.7804         |
| Masters                      | 156 | 31     | 0.8012         |
| PHD                          | 161 | 27     | 0.8323         |
| <b>Job Group</b>             |     |        |                |
| A (I-V)                      | 373 | 120    | 0.6783         |
| B (VI-X)                     | 78  | 22     | 0.7179         |
| C (XI-XV)                    | 360 | 79     | 0.7805         |
| D (XVI-XX)                   | 2   | 1      | 0.5            |

### 3.4 Model selection

To get an appropriate cox model and to decide which variable to include in the final model, the AIC procedure for variable selection was used. The procedure was carried out using the Stepwise AIC method in R software. After carrying out the Stepwise AIC model selection, the variables to be included in the final model are the ones that their AIC is greater than the original AIC of the full model. In this study, the selected variables to include in the final model are Job group, age group and terms of employment.

$$Surv(T, E) \sim X_2 + X_4 + X_7 \tag{7}$$

- T – Time in months
- E – Employment status
- $X_2$  – Age group
- $X_4$  – Terms of employment
- $X_7$  – Job group

### 3.5 Multivariate cox proportional hazard model

$H_0$ : There is no significant relationship between the selected covariates (Job group, Age group and Terms of Employment) on the survival time of the staff.

The results in Table 3 above show the final Cox PH model which can be expressed as can be:

$$h(t | X) = \exp(-0.3106 \cdot \text{JobGroupB} - 0.3334 \cdot \text{JobGroupC} - 2.0923 \cdot \text{JobGroupD} + 1.5443 \cdot \text{AgeGroup26} - 35 + 1.3827 \cdot \text{AgeGroup36} - 50 + 1.9903 \cdot \text{AgeGroup51} - 75 - 3.9198 \cdot \text{Permanent})$$

The overall p value of the model was  $P < 0.0001$  which is less than 0.05. This indicates that we reject the null hypothesis and conclude that there is a significant relationship between the covariates (Job Group, Age group and Terms of Employment) and the survival time of the staff.

**Table 3. ANOVA table of the multivariate cox proportional hazard model**

| Factor           | Coef ( $\beta$ ) | HR = exp ( $\beta$ ) | P Value |
|------------------|------------------|----------------------|---------|
| <b>Job Group</b> |                  |                      |         |
| A (I-V)          |                  | As reference         |         |
| B (VI-X)         | -0.3106          | 0.7330               | 0.1959  |
| C (XI-XV)        | -0.3334          | 0.71645              | 0.0365  |
| D (XVI-XX)       | -2.0923          | 0.1234               | 0.0398  |
| <b>Age Group</b> |                  |                      |         |
| 18-25            |                  | As reference         |         |

| Factor                     | Coef ( $\beta$ ) | HR = exp ( $\beta$ ) | P Value |
|----------------------------|------------------|----------------------|---------|
| 26-35                      | 1.5443           | 4.68471              | 0.00182 |
| 36-50                      | 1.3827           | 3.9856               | 0.00487 |
| 51-75                      | 1.9903           | 7.3180               | <0.0001 |
| <b>Terms of Employment</b> |                  |                      |         |
| Contract                   |                  | As reference         |         |
| Permanent                  | -3.9198          | 0.01984              | <0.0001 |

### 3.6 Comparison of the cox PH and weibull AFT models

$H_0$ : The Cox PH model is more appropriate than the Weibull AFT model for data fitting in this study.

Results in Table 4 show that the AFT Weibull model gives smaller parameter standard errors and smaller p values as compared to the Cox PH model indicating a potentially better fit when assuming a constant shape of the hazard function over time. Therefore, we reject the null hypothesis and accept the alternative hypothesis that, the Weibull AFT model is more appropriate than the Cox PH model for data fitting in this study.

**Table 4. Comparison of cox PH model and the weibull AFT model**

| Factor                     | Cox PH Model<br>Parameter Estimate (s.e); P value | Weibull AFT Model<br>Parameter Estimate (s.e); P value |
|----------------------------|---|--|
| <b>Intercept</b>           |   | 0.2338; <2e-16   |
| <b>Age Bracket</b>         |   |  |
| 26-35                      | 0.4952; 0.00182                                   | 0.2388; 0.00036  |
| 36-50                      | 0.4911; 0.00487                                   | 0.2385; 0.00254  |
| 51-75                      | 0.4917; 5.17e-05                                  | 0.2386; 3e-05  |
| <b>Terms Of Employment</b> |   |  |
| Permanent                  | 0.2029; <2e-16                                    | 0.0904; <2e-16   |
| <b>Job Group</b>           |   |  |
| B (VI-X)                   | 0.2401; 0.1959                                    | 0.1186; 0.1983   |
| C (XI-XV)                  | 0.1595; 0.0365                                    | 0.0784; 0.08373  |
| D (XVI-XX)                 | 1.018; 0.0398                                     | 0.5025; 0.0407   |

Since the Weibull AFT model gives the best fit compared to the Cox PH model, the Weibull results are used to fit the Survival function and the hazard function of staff as shown below.

The Weibull survival function is shown by equation (5).

And the hazard function is:

$$h_T(t) = \alpha\lambda^\alpha t^{\alpha-1} \tag{8}$$

Where  $\alpha$  is the shape parameter, and  $\lambda$  is the scale parameter. In the Weibull regression, the log(scale) parameter is given, which can be used to find  $\lambda$ .

From the provided results:

$$\log(\text{scale}) = -0.7003$$

$$\text{scale} = 0.496 \text{ (this is derived from } \text{scale} = e^{\log(\text{scale})} \text{)}$$

The intercept and coefficients for different factors will adjust the scale parameter  $\lambda$  for each individual based on their covariates.

Given scale = 0.496, the shape parameter  $\alpha$  is typically taken as  $1/\text{Scale}$ . Therefore:

$$\alpha = 1/0.496 \approx 2.0161$$

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The scale parameter  $\lambda$  for a specific individual is adjusted by the exponentiated sum of the intercept and the covariates which is given by:

$$\lambda = \exp(\text{intercept} + \sum (\text{coefficients} \times \text{covariates}))$$

In our case, the scale parameter  $\lambda$  is given by:

$$\lambda = \exp(4.1279 + (-0.8528 \cdot \text{Age}26 - 35) + (-0.7200 \cdot \text{Age}36 - 50) + (-0.9954 \cdot \text{Age}51 - 75) + (2.2320 \cdot \text{EmploymentPermanent}) + (0.1526 \cdot \text{JobGroupB}) + (0.1355 \cdot \text{JobGroupC}) + (1.0282 \cdot \text{JobGroupD}))$$

The survival function then becomes:

$$S_T(t) = \exp(-[\exp(4.1279 + (-0.8528 \cdot \text{Age}26 - 35) + (-0.7200 \cdot \text{Age}36 - 50) + (-0.9954 \cdot \text{Age}51 - 75) + (2.2320 \cdot \text{EmploymentPermanent}) + (0.1526 \cdot \text{JobGroupB}) + (0.1355 \cdot \text{JobGroupC}) + (1.0282 \cdot \text{JobGroupD})) \cdot t]^{2.0161})$$

In this case,  $t$  represents the time at which the probability of survival is being evaluated.

The Weibull Hazard function in equation (8) is then given as:

$$h_T(t) = 2.0161 \times [\exp(4.1279 + (-0.8528 \cdot \text{Age}26 - 35) + (-0.7200 \cdot \text{Age}36 - 50) + (-0.9954 \cdot \text{Age}51 - 75) + (2.2320 \cdot \text{EmploymentPermanent}) + (0.1526 \cdot \text{JobGroupB}) + (0.1355 \cdot \text{JobGroupC}) + (1.0282 \cdot \text{JobGroupD}))]^{2.0161} \times t^{1.0161}$$

In this case,  $t$  represents the time at which the hazard rate (the instantaneous risk of the event occurring) is being evaluated.

These equations provide the survival and hazard functions for an individual based on their covariate values using the Weibull model parameters.

## 4 Conclusion

The Kaplan Meier non-parametric estimator was used to estimate the Survival Probabilities of given group of staff. Once the variables were selected using the step AIC function of Mass Library in R, the final model included Age group, Terms of Employment, and Job group. These variables are important for the study of staff survival time in service at Chuka University. The results on the Univariate Cox PH Model showed that the covariates, gender, age group, terms of employment, staff category, highest qualification, and Job group were statistically significant at 5% level of significance, with the exception of the Marital status, which was insignificant. The findings from the study for example showed that the male staff have high survival probability compared to their female counterparts: the younger employees between the age of 18-25 stay in service for fewer years compared to those between the age of 26-35 and 36-50. To check for the survival time of individual staff, the Parametric Weibull AFT model was used. The study also compared the results of Cox Proportional Hazard model from those of Weibull AFT model. To achieve this, the selected covariates of time to exit were fitted in the two models and their performance was compared using the standard errors. The Weibull AFT model was found to give the best model fit with more precise estimates that had small standard errors compared to the Cox Proportional Hazard Model.

## Disclaimer (Artificial Intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

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## Competing Interests

Authors have declared that no competing interests exist.

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