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Comparing the Performance of Weibull, Log-Logistics and Gompertz Survival Models on Oncological Data

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ABSTRACT

Cancer is a general term used for a group of diseases that cause abnormal cells to divide without control and overpass other tissues. In addition, if they expand out of control, cancer can result in death, an estimated 14.1 million new cases of cancer and 8.2 million deaths from cancer occurred in 2012 in both sexes. The general aim of the research was to compare the performance of Weibull, Log-logistics and Gompertz survival models on oncological data. The research methodology adopted cases on oncological study was used in this study, obtained from internet sources and publications. Descriptive Statistics of dataset was performed using mean, median, mode, variance, skewness, and kurtosis. Parametric survival models were used in the analysis. The models of Weibull, Log-logistics and Gompertz models were chosen because of their similarities in order to have better basis for comparison and also have differences that will cater to the situation where the other one fails. The models are to be fitted to the data with the view to find the best fit, R statistical package was used in analyzing the data. The result revealed that the maximum likelihood estimates of dataset2 with 3 with different model fit, all the information criteria and log-likelihood of the models, Gompertz model has smallest value in all the information criteria, which indicates that Gompertz model is the best fitted model to Myelogenous leukemia data. It also shows the maximum likelihood estimates of dataset 1 with 3 with different model fit, all the information criteria and log-likelihood of the models. Weibull and Log-logistic models have smallest value in all the information criteria, indicating that Weibull and log-logistic models perform better than Gompertz model in fatigue fracture data. The research concludes that Gompertz model is the best fitted model to Remission Times of Bladder Cancer patients' data, and Gompertz distribution is the best fit distribution for the data and that Gompertz model and Gompertz distribution is also the best fit to Myelogenous leukemia data. It recommended that Gompertz model is the best fit in the oncological data, followed by the Log-logistic model, Weibull and Log-logistic model behave similarly on the dataset.

Keywords: data; cancer; performance; models; comparison and similarities

INTRODUCTION

Cancer is a general term used for a group of diseases that cause abnormal cells to divide without control and overpass other tissues. In addition, if they expand out of control, cancer can result in death. Abouammoh et al. (2021) posited that an estimated 14.1 million new cases of cancer and 8.2 million deaths from cancer occurred in 2012 in both sexes. Estimation of 5-year prevalent cases in 2012 showed that there were 32.5 million people (adult population) alive from both sexes who had a cancer diagnosed during the previous years (Ferlay et al., 2014; Ibrahim and Abdullahi, 2016; Adebola, et. al., 2018). According to the Global Burden of Disease (2011) (GBD) study, the estimated rate of Disability-Adjusted Life Years (DALY) attributed to all neoplasms in both sexes worldwide was 2,793 (95% UI: 2,580-2,985) in 1990, which decreased over the time and finally reached 2,736 (95% UI: 2,532-2,889) in 2010. Every patient demonstrates the loss of one year of healthy life (Ibrahim, et al., 2022a). In addition, 7.6% of global DALYs are assigned to the neoplasms (Ibrahim, et al., 2022b and Ibrahim, et al., 2022c).

The three most leading cancers in both sexes worldwide were lung cancer (13% of the total), breast cancer (11.9%) and colorectal cancer (9.7%); the most common types of cancer in men, respectively, are lung cancer (16.8%), prostate cancer (14.8%) and colorectal cancer (10.1%) while in women they are ordered as breast cancer (25.1%), colorectal cancer (9.2%) and lung cancer (8.8%) (Ferlay et al., 2014; Ibrahim, 2020a; Ibrahim, 2020b).

Conceptual Framework

The occurrence of survival (or time-to-event) data is commonplace in medical research, where interest lies in the time it takes from a given baseline, for an event of interest to occur, and the factors that are associated with it. For example, this could be the effect of a treatment on the time to death since diagnosis of cardiovascular disease.

The two main approaches to survival analysis, are the semi-parametric approach of Cox, and fully parametric approaches, assuming such distributions as the exponential or Weibull, for example (Abouammoh et al. 2021; Ibrahim, et al., 2022a).

The Cox model does not assume any functional form for the baseline hazard function, whereas a parametric approach assumes a specific shape, estimated as part of the model. Both allow us to investigate the influence that risk factors have on the rate of disease or mortality, for example. In this research we would want to concentrate on the parametric approach to survival analysis, in particular, deriving a general algorithm to simulate survival data under more biologically plausible scenarios to better assess both methods used in practice, and novel models (Feigl and Zelen, 1995; Ibrahim and Abdullahi, 2019; Ibrahim, et al., 2022b). This then leads to the development of a general framework for parametric survival analysis, motivated by wanting to incorporate greater flexibility than standard parametric models can provide, particularly in capturing complex baseline hazard functions and time-dependent effects. The framework is extended to incorporate cluster robust standard errors and relative survival, with an improved estimation routine when using the special case of restricted cubic splines to model the baseline and time-dependent effects, illustrated with applications in the areas of breast and bladder cancer (Ibrahim and Falola, 2021; Ibrahim, et al., 2022c).

Survival Analysis

Survival analysis is a commonly-applied statistical method in medical research. It is used for time-to-event analysis where patients are followed up to see whether, and when, they experience an event of interest. In the standard (noncompeting risks) survival analysis setting there is one event of interest, such as any-cause mortality or a composite outcome combining a non-fatal event and death (Ibrahim and Abdulkadir, 2019; Muhammad, et. al., 2023). Typical approaches used for analysis include the Kaplan-Meier survival estimator and Cox proportional hazard regression modelling. However, often there are situations where patients are at risk of two or more mutually exclusive events, which affect the risk of each other, and this requires a different approach. In such situations there is a competing risks scenario. The risks are said to be "competing" with each other to be the first event. For instance, two different causes of death act as competing risks because only one of them can occur. Another example of competing risks are hospital discharge and in-hospital infection, in that discharge affects the risk of in-hospital infection by preventing it occurring first. There has been a wealth of literature that provides an overview of the competing risks method in both the medical statistics/clinical epidemiology field (Feigl and Zelen, 1995; Ferlay et. al., 2014; Ibrahim, et.al., 2022). Most of the contributions giving such an overview provide a formal definition of a competing risk. A commonly used definition of a competing risk is that it is an event that precludes an event of interest. This is the sole definition used in the work by Abouammoh et al. (2021) and Ibrahim and Adamu, (2020). However, this definition does not convey every scenario in which competing risks can be present. It implies only deaths can be competing risks. Gould, et al. (2014), used the more comprehensive definition that a competing risk is an event that precludes the event of interest, or otherwise modifies the probability of experiencing the event of interest. Therefore, they recognise that competing risks need not be limited to deaths, and that non-fatal events can also act as competing risks. Similarly, Oguntade et al. (2016) and Ibrahim, (2019) used the definition that a competing risk prevents the event of interest occurring first, acknowledging that competing risks consist of non-fatal events and/or deaths. To help fully understand the definition of a competing risk, common competing risks scenarios. The scenarios outlined are primarily based on the scenarios described in the tutorial by Andrews and Herzberg, (2020).

It is important to recognize a competing risks scenario, when one exists, as this requires a different approach to standard survival analysis, it should be noted that, while there are many useful contributions that define and illustrate competing risks scenarios, there are other articles in the literature that portray competing risks in a confusing and often misleading way. For example, Andrews and Herzberg, (2020) state that "the occurrence of a specific event would preclude the competing risks from being observed". This is not inaccurate in itself because a specific event is considered a competing risk when in fact the competing risk is treated as the event of interest. However, it does not follow the usual convention that it is the competing risk that precludes, or otherwise alters the probability of, the event of interest and not the other way around. In other work, Gieser, et al. (2018) and Ibrahim, et. al., (2017) include the semi-competing risks approach in their review of statistical methods for competing risks. This introduces confusion as the semi competing risks approach, they present is not used for competing risks scenarios. It does not just consider the first event to occur from two or more mutually exclusive events. Instead, this approach also considers subsequent events. It is often known as an "illness-death model", part of the more general multi-state modelling framework.

RESEARCH METHODOLOGY

Data cases on oncological study is used in this study, obtained from internet sources and publications. Descriptive Statistics of dataset is performed using mean, median, mode, variance, skewness, and kurtosis. Parametric survival models are used in the analysis. The models are Weibull, Log-logistics and Gompertz models, the models are chosen because of their similarities in order to have better basis for comparison and also have differences that will cater to the situation where the other one fails. The models are to be fitted to the data with the view to find the best fit. R statistical package is used for analyzing the data.

DATA ANALYSIS AND PRESENTATION

The main purpose of this research was to assess comparative study on the performance of Weibull, log-logistic and Gompertz survival models on oncological data.

Put in another form, this study set out to assess the independent variables of the performance of Weibull, log-logistic and Gompertz survival model, been the dependent variable among oncological data.

This presents the statistical results and findings of the research variables specified in the research methods and procedures. Specifically, the data analysis was in line with specific objectives of the study on the various sections. Basically, secondary data was used for the analysis.

TABLE 1: Descriptive Statistics of the Variables.

Data	Mean	Median	Mode	Variance	Skewness	Kurtosis	Minimum	Maximum	n
1	9.36562	6.395	5	110.425	3.28657	15.4831	0.08	79.05	128
2	17.6325	12.401	5	252.572	1.06609	0.10351	0.03	60.625	101
3	1.34144	0.841	0.25	1.55401	0.97215	-0.3362	0.047	4.033	45
4	1.95924	1.7362	1.5	2.47741	1.97956	5.16079	0.0251	9.096	76
5	0.8526	0.9	0.7,0.9	0.11201	0.17219	0.31555	0.1	2	346

Source: Field Survey, 2023.

Table 1 shows the description of data used in the analysis, dataset 1 through 5 are Remission Times of Bladder Cancer Patients, Myelogenous leukemia data, Survival times of a group of patients given chemotherapy, Fatigue Fracture data, and Nicotine measurements respectively, the table presents measures of location using the mean, median mode and measures of dispersion using variance, skewness, and kurtosis, the minimum, maximum and the sample sizes are also presented.

TABLE 2: MLE's and Information Criteria of models for Remission Times of Bladder Cancer Patients.

Model	$\hat{\alpha}$	$\hat{\beta}$	AIC	CAIC	BIC	HQIC	LL
Weibull	1.96431	1.12646	932.452	932.548	938.156	934.769	464.226
Log-logistic	1.964312	1.126458	932.4515	932.5475	938.1556	934.7691	464.2258
Gompertz	0.024758	1.5861422	903.9576	904.0536	909.6616	906.2752	449.9788

Source: Field Survey, 2023.

Table 2 shows the maximum likelihood estimates of dataset 1 with 3 with different model fit, all the information criteria and log-likelihood of the models indicate that, Gompertz model has smallest value in all the information criteria, indicating that Gompertz model is the best fitted model to Remission Times of Bladder Cancer patient's data.

TABLE 3: One Sample test about the distribution of dataset for Remission Times of Bladder Cancer Patients (Dataset1).

Distribution	W	A	Kolmogorov-Smirnov test	
			D	p-value
Weibull	0.2664455	1.593023	0.59415	< 2.2e-16
Log-logistics	0.1770686	1.174072	0.40853	< 2.2e-16
Gompertz	0.3032234	1.804689	0.3568	1.399e-14

Source: Field Survey, 2023.

Table 3 presents the Cramer-von Misses (W), the Anderson Darling (A) and the Kolmogorov Smirnov (D) statistics, it is observed that the Gompertz distribution has greater p-value than other distributions, indicating that Gompertz distribution is the best fit for Remission Times of Bladder Cancer Patients.

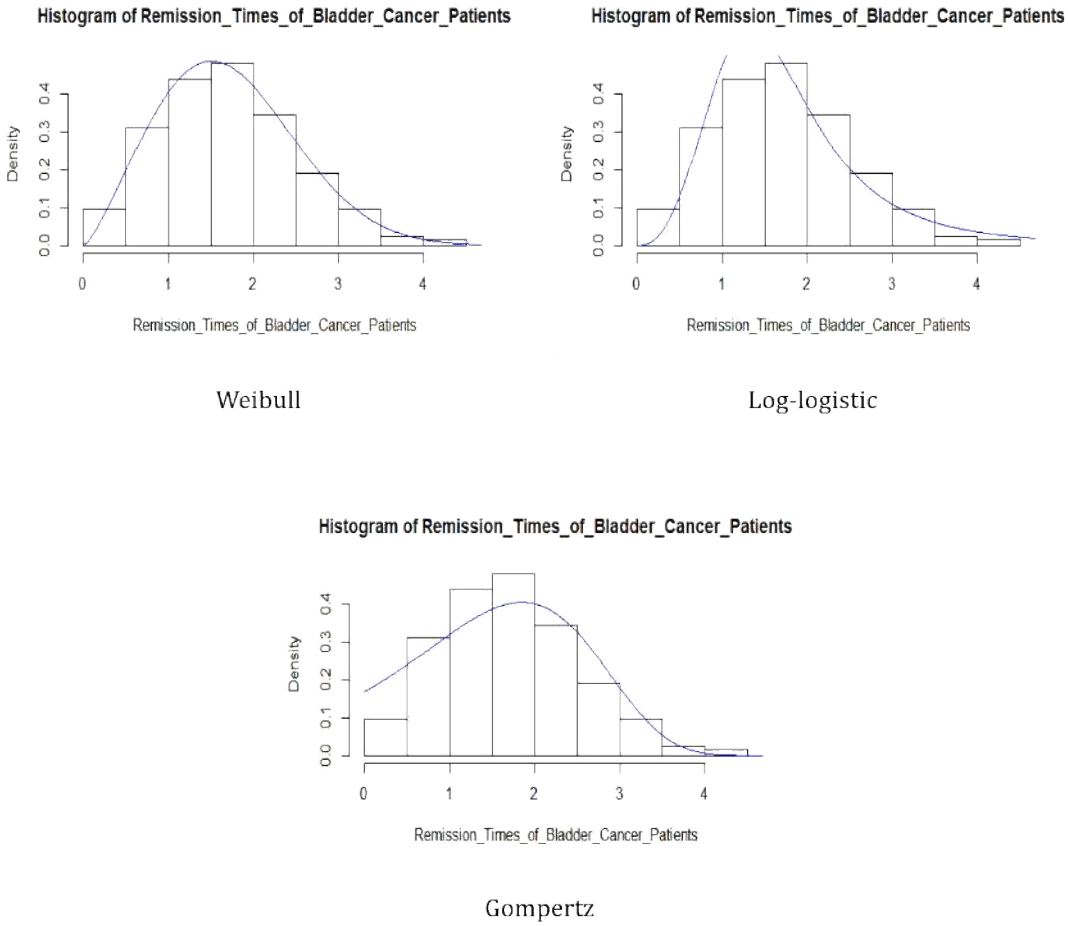


FIGURE 1: Fitted curve of the three distributions for Remission Times of Bladder Cancer Patients.

Survival Analysis of Myelogenous Leukemia Data

TABLE 4: MLE's and Information Criteria of models for Myelogenous leukemia.

Model	$\hat{\alpha}$	$\hat{\beta}$	AIC	CAIC	BIC	HQIC	LL
Weibull	1.98536	0.83554	918.609	918.732	923.840	920.727	457.304
Log-logistic	1.9853681	0.836643	918.6094	918.7319	923.8397	920.7268	457.3047
Gompertz	0.0261552	1.673465	795.9594	796.0818	801.1896	798.0767	395.9797

Source: Field Survey, 2023.

Table 4 shows the maximum likelihood estimates of dataset2 with 3 with different model fit, all the information criteria and log-likelihood of the models, Gompertz model has smallest value in all the information criteria, which indicates that Gompertz model is the best fitted model to Myelogenous leukemia data.

TABLE 5: One Sample test about the distribution of dataset for Myelogenous leukemia data.

Distribution	W	A	Kolmogorov-Smirnov test	
			D	p-value
Weibull	0.05147	0.40237	0.66589	< 2.2e-16
Log-logistics	0.3082024	1.957631	0.46635	< 2.2e-16
Gompertz	0.1523498	0.9057371	0.10096	0.2547

Source: Field Survey, 2023.

Table 5 presents the Cramer-von Misses (W), the Anderson Darling (A) and the Kolmogorov Smirnov (D) statistics, it is observed Gompertz distribution has greater p-value than other distributions, implying that the Gompertz distribution is the best fit for Myelogenous leukemia data.

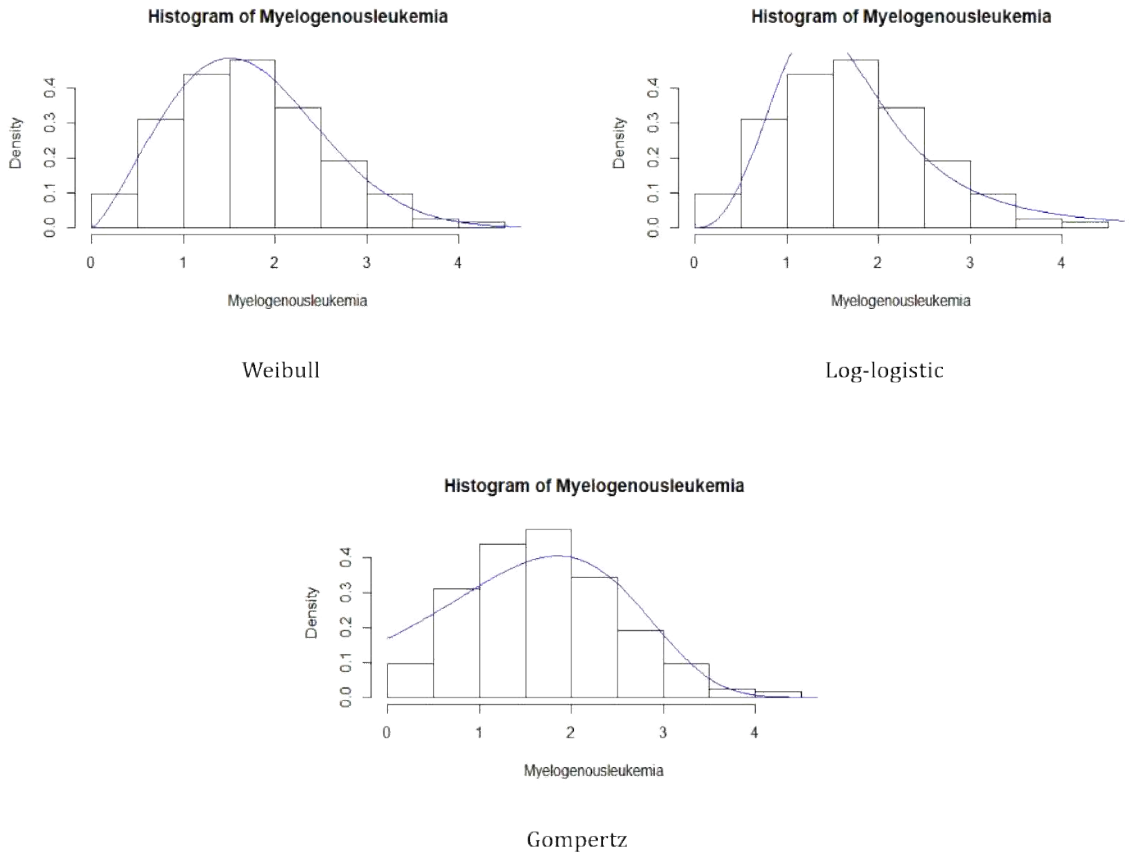


FIGURE 2: Fitted curve of the three distributions for myelogenous leukemia data.

Survival Analysis on Survival Times of a Group of Patients Given Chemotherapy Treatment

TABLE 6: MLE's and Information Criteria of models for survival times of a group of patients given chemotherapy treatment.

Model	$\hat{\alpha}$	$\hat{\beta}$	AIC	CAIC	BIC	HQIC	LL
Weibull	0.833042	1.487036	124.384	124.6697	127.9973	125.731	60.19198
Log-logistic	0.833042	1.487036	124.384	124.6697	127.9973	125.731	60.19198
Gompertz	0.258314	1.974204	121.377	121.6630	124.9906	122.7243	58.68863

Source: Field Survey, 2023.

Table 6 shows the maximum likelihood estimates of dataset 3 with 3 with different model fit, all the information criteria and log-likelihood of the models, Gompertz model has smallest value in all the information criteria, indicating that Gompertz model is the best fitted model to survival times of a group of patients given chemotherapy treatment data.

TABLE 7: One Sample test about the distribution of dataset for survival times of a group of patients given chemotherapy treatment (Dataset3).

Distribution	W	A	Kolmogorov-Smirnov test	
			D	p-value
Weibull	0.13391	0.87063	0.27477	0.00171
Log-logistics	0.08041826	0.5569135	0.087438	0.8519
Gompertz	0.1132596	0.742632	0.16673	0.146

Source: Field Survey, 2023.

Table 7 presents the Cramer-von Misses (W), the Anderson Darling (A) and the Kolmogorov Smirnov (D) statistics, Log-logistic distribution has greater p-value than other distributions, hence it is the best fit for survival times of a group of patients given chemotherapy treatment.

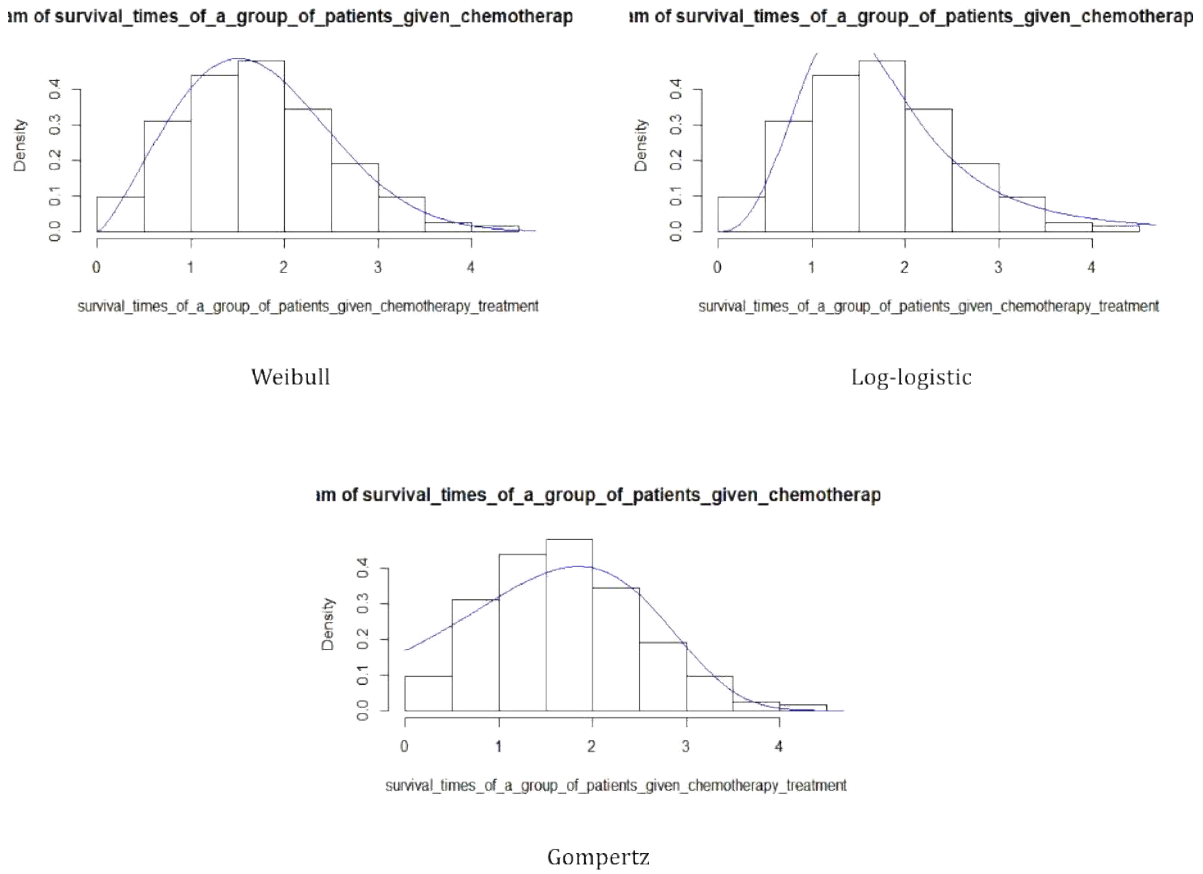


FIGURE 3: Fitted curve of the three distributions on survival times of a group of patients given chemotherapy treatment.

Survival Analysis on Fatigue Fracture Data

TABLE 8: MLE's and Information Criteria of models for Fatigue Fracture data (Dataset4).

Model	$\hat{\alpha}$	$\hat{\beta}$	AIC	CAIC	BIC	HQIC	LL
Weibull	1.565866	1.963127	252.9542	253.1185	257.6156	254.8171	124.4771
Log-logistic	1.565866	1.963127	252.9542	253.1185	257.6156	254.8171	124.4771
Gompertz	0.197519	1.880304	256.6414	256.8058	261.3029	258.5044	126.3207

Source: Field Survey, 2023.

Table 8 shows the maximum likelihood estimates of dataset 1 with 3 with different model fit, all the information criteria and log-likelihood of the models. Weibull and Log-logistic models have smallest value in all the information criteria, indicating that Weibull and log-logistic models perform better than Gompertz model in fatigue fracture data.

TABLE 9: One Sample test about the distribution of dataset for fatigue fracture (Dataset4).

Distribution	W	A	Kolmogorov-Smirnov test	
			D	p-value
Weibull	0.2666667	1.529223	0.22099	0.0009683
Log-logistics	0.1526425	0.9209887	0.099912	0.4073
Gompertz	0.2328952	1.331934	0.11856	0.2178

Source: Field Survey, 2023.

Table 9 presents the Cramer-von Misses (W), the Anderson Darling (A) and the Kolmogorov Smirnov (D) statistics. Log-logistic distribution has greater p-value than other distributions indicating that the log-logistic distribution is the best fit for fatigue fracture data.

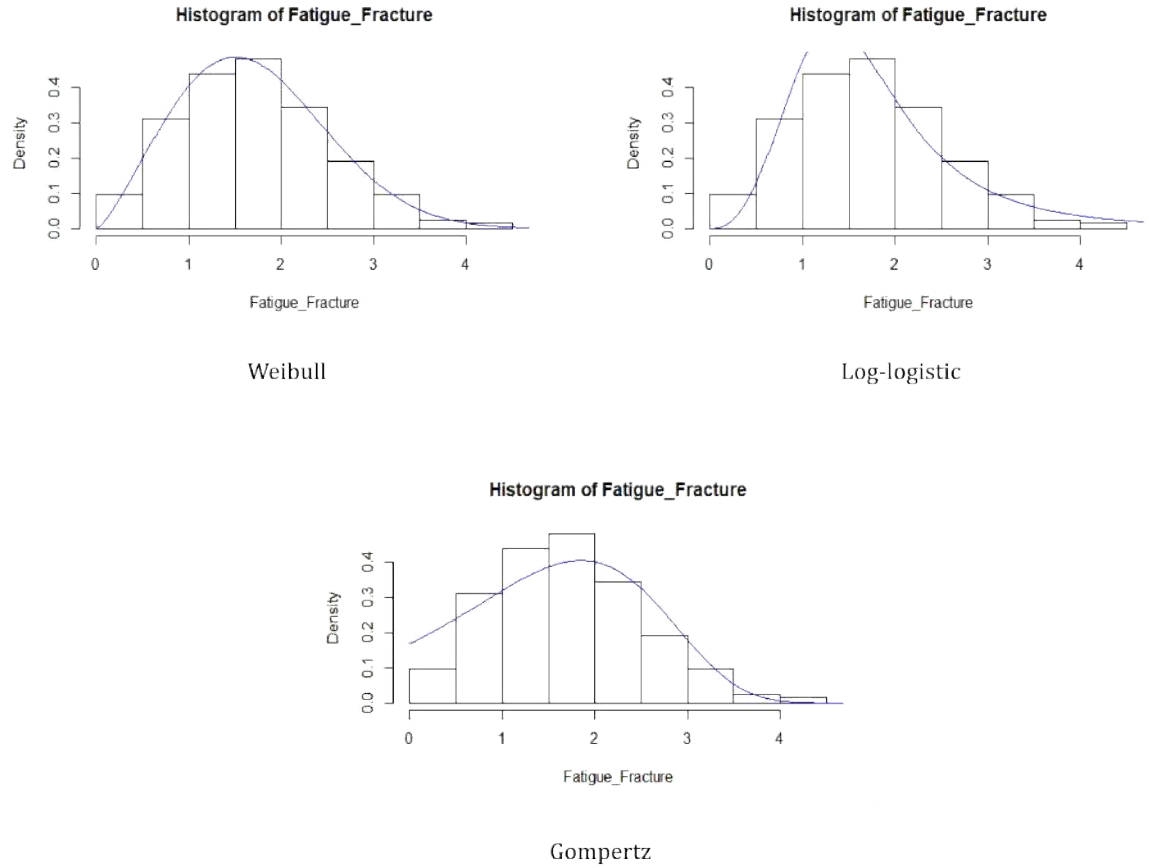


FIGURE 4: Fitted curve of the three distributions on Fatigue Fracture Data.

Survival Model for Nicotine Measurements

TABLE 10: MLE's and Information Criteria of models for nicotine measurements (Dataset5).

Model	$\hat{\alpha}$	$\hat{\beta}$	AIC	CAIC	BIC	HQIC	LL
Weibull	0.869319	1.972623	462.84	462.875	470.5329	465.9033	229.42
Log-logistic	0.869319	1.972623	462.84	462.875	470.5329	465.9033	229.42
Gompertz	1.796779	0.217613	284.43	284.469	292.1264	287.4968	140.22

Source: Field Survey, 2023.

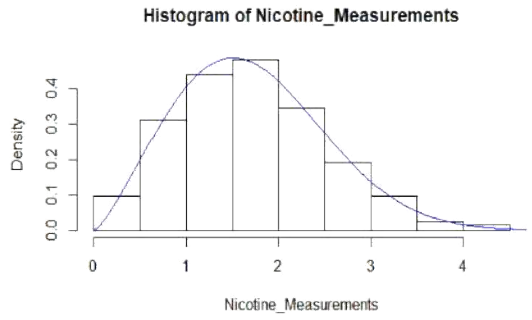
Table 10 shows the maximum likelihood estimates of dataset 5 with 3 with different model fit, all the information criteria and log-likelihood of the models. Gompertz model has smallest value in all the information criteria, indicating that Gompertz model is the best fitted model to nicotine measurements data.

TABLE 11: One Sample test about the distribution of dataset for nicotine measurement (Dataset5).

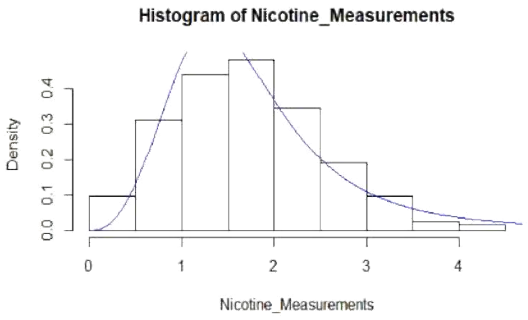
Distribution	W	A	Kolmogorov-Smirnov test	
			D	p-value
Weibull	0.6492512	3.774388	0.22814	4.441e-16
Log-logistics	1.582193	9.350919	0.25369	< 2.2e-16
Gompertz	0.4903747	2.944429	0.17034	3.807e-09

Source: Field Survey, 2023.

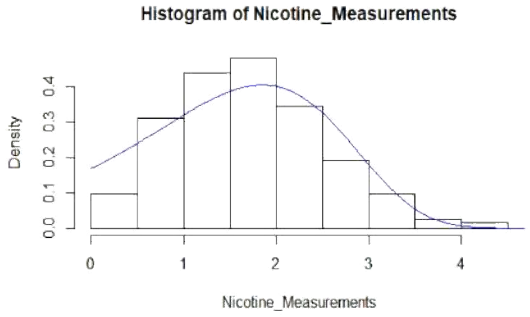
Table 11 presents the Cramer-von Misses (W), the Anderson Darling (A) and the Kolmogorov Smirnov (D) statistics, Gompertz distribution has greater p-value than other distributions, therefore Gompertz distribution is the best fit for nicotine measurements.



Weibull



Log-logistic



Gompertz

FIGURE 5: Fitted curve of the three distributions on nicotine measurements.

SUMMARY OF FINDINGS

Based on the analysis carried out, the following findings were made;

- Gompertz model is the best fitted model to Remission Times of Bladder Cancer patients' data, and Gompertz distribution is the best fit distribution for the data.
- Gompertz model and Gompertz distribution is also the best fit to Myelogenous leukemia data.
- Gompertz model is the best fitted model to survival times of a group of patients given chemotherapy treatment data, while log-logistic distribution is the best fit distribution for the data.
- Weibull and log-logistic models perform better than Gompertz model in fatigue fracture data, while log-logistic distribution is the best fit for the data.
- Gompertz model and the distribution is the best fit to nicotine measurements.

CONCLUSION

Based on the analysis carried out, it was concluded that Gompertz model was the best fit in the oncological data, followed by the Log-logistic model, Weibull and Log-logistic model behave similarly on the dataset.

RECOMMENDATION

From the research it has shown that most of the research conducted on oncological data (cancer related cases) has shown that there is scarcity of research on related cases on survival model that can best be used to model cancer related data.

The research was able to identify a parametric that can best be used to model cancer data known as Gompertz model was the best used model on the research. The research will enable other researcher such as medical personnel to model or know the best model on cancer related cases.

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