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Comparative Analysis of Weibull and Loglogistic Regression Models in Predicting Length of Stay of Patients in Emergency Unit

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***Abstract**: This study compares the performance of Weibull and Loglogistic regression models in predicting Length of Stay (LOS) for patients in the Emergency Department (ED) of General Hospital Damatu, Yobe State, Nigeria, using data from January 2022 to December 2023. The aim was to identify the most effective statistical model based on predictive accuracy and model fit criteria. Data included patient demographics, medical history, arrival times, and other relevant variables. Likelihood ratio tests and model fit statistics such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed for evaluation. The results indicate that while the Weibull model demonstrated stronger effects on certain predictors like Age and Gender, the Loglogistic model consistently exhibited superior overall performance with lower AIC (155.05) and BIC (199.22) scores compared to Weibull (AIC = 184.92, BIC = 229.09). Furthermore, the Loglogistic model presented fewer unusual residuals and higher log-likelihood (-68.527) relative to Weibull (-83.459), suggesting better fit and predictive accuracy. Key factors influencing LOS included Age, Gender, Time of Arrival, Previous ED Visits, and ED Crowding. These findings highlight the Loglogistic regression model as the preferred choice for predicting LOS in the ED setting.*

***Keywords:** Weibull Regression, Loglogistic Regression, Hospital Length of Stay, Emergency Department*

Introduction

The Length of Stay (LOS) is defined as the number of days a patient remains hospitalized (Han *et al.,* 2022). It is a critical metric for assessing hospital performance, as shorter stays can reduce per-discharge costs and transition care to more cost-effective post-acute settings. Additionally, shorter LOS can lead to more efficient resource allocation, lower readmission rates, and improved overall service efficiency. As a measurable parameter, LOS is crucial for evaluating healthcare resource utilization, underscoring its importance in health resource management (Burgess *et al*., 2022).

Predicting LOS for inpatients is a challenging yet vital task for the operational success of hospitals. With limited resources, the ability to forecast LOS is invaluable for administrators in planning and managing resources effectively (Schneider *et al*., 2021). LOS is a critical measure of healthcare utilization and a determinant of hospitalization costs, aligning with efforts to control healthcare expenses. Despite the complexities, predicting LOS is essential for resource planning, especially given the increasing volume of clinical data from trials, electronic patient records, and computer-supported disease management (Fink *et al*., 2020).

Kim and Lee (2022) highlight the complexity of managing patient flow in hospital Emergency Departments (EDs), largely due to the variable LOS experienced by patients. The unpredictable nature of ED admissions necessitates a thorough understanding of the factors influencing LOS to optimize resource allocation and enhance healthcare delivery efficiency (Lucero *et al*., 2021). The existing literature recognizes the complex nature of ED operations and the need for sophisticated modeling techniques to predict and manage patient LOS (Rizk *et al.,* 2021). Weibull Regression analysis emerges as a valuable statistical tool, capable of interpreting the diverse variables contributing to LOS variations.

As healthcare institutions strive to provide timely and effective emergency care, applying advanced statistical models becomes imperative (Hick *et al.*, 2021). The scarcity of studies specifically focusing on predicting hospital LOS using the Weibull Regression Model in the ED context highlights the need for this research. This study aims to bridge knowledge gaps by exploring this statistical methodology, offering insights that contribute to targeted interventions, improved patient care, and efficient utilization of healthcare resources within EDs (Johnson *et al.,* 2021).

The Length of Stay (LOS) in healthcare facilities is influenced by various factors, presenting challenges in resource management and patient flow. Predicting LOS is critical for optimizing resource utilization, improving service quality, and managing costs effectively. It is a key metric for assessing surgical success and controlling healthcare expenditures through strategies like bundled payments. Various statistical frameworks and advanced methods such as machine learning and natural language processing have been explored to enhance LOS prediction accuracy using large datasets and electronic health records. Standardized variables and dynamic models show significant potential for precise predictions across different healthcare settings, emphasizing the need for comprehensive analytical approaches beyond clinical parameters (Ellahham & Ellahham, 2019; McGrath *et al*., 2021; Annis *et al*., 2020; Thakur *et al*., 2023; Murai *et al*., 2021; Smith *et al.,* 2023; Lee *et al.,* 2022; Alam *et al*., 2023; Hyland *et al*., 2023; Catling & Wolff, 2020; Xu *et al*., 2022).

This study aims to rigorously evaluate and compare the predictive capabilities of two distinct survival regression models, namely the Weibull Regression and Loglogistic Regression models, in forecasting the Length of Stay (LOS) for patients within Emergency Departments (EDs). The research employs sophisticated statistical methodologies tailored to survival analysis, seeking to enhance the precision and reliability of LOS predictions.

Aim and Objectives

The aim of this study is to determine the most effective statistical model for predicting the Length of Stay (LOS) of patients in Emergency Departments by comparing the performance of Weibull Regression and Log logistic Regression models. The specific objectives are to:

1) Evaluate and Compare the Predictive Accuracy of Weibull and Log logistic Regression Models Emergency Department (ED) of General Hospital Damatu, Yobe State, Nigeria between January 2022 and December, 2023.
2) Identify Key Factors Influencing LOS in Emergency Department (ED) of General Hospital Damatu, Yobe State, Nigeria between January 2022 and December, 2023.
3) Provide Evidence-Based Recommendations for Hospital Administrators and Policymakers.

Methodology

will be collected from the electronic health records of patients admitted to the ED of General Hospital Damatu from January 2022 to December 2023. The dataset will include patient demographics, medical history, diagnosis, treatment procedures, and discharge dates. The LOS will be calculated as the number of days between admission and discharge.

Model Specification

Weibull Regression Model

The Weibull Regression model is defined by the hazard function:

$$h(t) = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} \quad (1)$$

where t is the time (LOS), λ is the scale parameter, and k is the shape parameter. The survival function for Weibull regression is given by:

$$S(t) \exp\left[-\left(\frac{t}{\lambda}\right)^{k}\right] \quad (2)$$

The log-likelihood function for Weibull Regression is:

$$\ln L = \sum_{i=1}^{n} \delta_i \left[\ln k + (k-1)\ln\left(\frac{t_i}{\lambda}\right) - \left(\frac{t_i}{\lambda}\right)^{k}\right] \quad (3)$$

Where δ_i is the censoring indicator (1 if the event is observed, 0 is the event is censored) and t_i is the observed time.

Loglogistic Regression Model

The Loglogistic Regression model is defined by the hazard function:

$$h(t) = \frac{\left(\frac{\gamma}{\lambda}\right)\left(\frac{t}{\lambda}\right)^{\gamma-1}}{1+\left(\frac{t}{\lambda}\right)^{\gamma}} \quad (4)$$

where t is the time (LOS), λ is the scale parameter, and γ is the shape parameter.

The survival function for Loglogistic Regression is:

$$S(t) = \left[1+\left(\frac{t}{\lambda}\right)^{\gamma}\right]^{-1} \quad (5)$$

The log-likelihood function for Loglogistic Regression is:

$$\ln L = \sum_{i=1}^{n} \delta_i \left[\ln \gamma - \ln \lambda + (\gamma - 1) \ln t_i - (\gamma + 1) \ln \left(1 + \frac{t_i}{\lambda}\right)^{\gamma} \right] \quad (6)$$

where δ_i is the censoring indicator (1 if the event is observed, 0 if censored) and t is the observed time.

Dependent Variable: The dependent variable is the Length of Stay (LOS) for each patient in the Emergency Department.

Independent Variables

Age (x_1), gender (x_2), abnormal vital signs (x_3), time of arrival (x_4), previous medical history (x_5), previous ED visits (x_6), availability of inpatient beds (x_7), ED Crowding (x_8) and lab tests (x_9).

Model Selection Criteria: AIC and BIC

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used as a metrics in evaluating model performance. Both criteria aim to balance model fit and complexity, but they differ in their approach and sensitivity to model size.

Akaike Information Criterion (AIC)

The AIC is calculated as:

$$AIC = 2k - 2\ln(L) \quad (7)$$

Where

k is the number of parameters in the model.

$ln(L)$ is the log-likelihood of the model.

Bayesian Information Criterion (BIC)

The BIC is calculated as:

$$BIC = k\ln(n) - 2\ln(L) \quad (8)$$

Where:

k is the number of parameters in the model.

n is the number of observations.

$ln(L)$ is the log-likelihood of the model

Results

Table 1: Likelihood Ratio Tests of the Weibull and Loglogistic Regression Models

Factor	REGRESSION MODELS					
	Weibull Regression			Loglogistic Regression		
	Chi-Square	df	p-value	Chi-Square	df	p-value
Age	30.8531	1	p<0.01	27.8050	1	p<0.01
Gender	36.7738	1	p<0.01	44.4225	1	p<0.01
Abnormal Vital Sign	0.11343	1	0.7363	0.29090	1	0.5896
Time of Arrival	11.4658	1	p<0.01	7.77798	1	p<0.01
Previous Medical History	2.11844	1	0.1455	2.71442	1	0.0994
Previous Emergency Unit	42.9153	1	p<0.01	8.33365	1	p<0.01
Availability of Inpatient Bed	19.6701	1	p<0.01	16.63310	1	p<0.01
Emergency Department Crowding	22.5123	1	p<0.01	26.55090	1	p<0.01
Laboratory Test	0.49725	1	0.4807	2.52354	1	0.1122
-LL	-83.459			-68.527		
AIC	184.92			155.05		
BIC	229.09			199.22		

The analysis compares Weibull and Loglogistic regression models using Chi-Square values, degrees of freedom, and p-values for various factors, as well as overall model fit statistics like log-likelihood, AIC, and BIC. Both models identify Age, Gender, Time of Arrival, Previous Emergency Unit, Availability of Inpatient Bed, and Emergency Department Crowding as significant factors, with Weibull often showing stronger effects. However, the Loglogistic model exhibits a higher log-likelihood (-68.527 compared to -83.459) and lower AIC (155.05 compared to 184.92) and BIC (199.22 compared to 229.09) scores, indicating a better overall fit. Despite Weibull's stronger effects on some factors, the Loglogistic model had superior fit based on AIC and BIC makes it the preferable model overall.

Table 2: Unusual Residuals for time of the Weibull Regression Models

Row	*Y*	*Predicted Y*	*Residual*	*Standardized Residual*	*Cox-Snell Residual*
3	19.0	31.709	-12.709	0.02	0.0166
4	18.0	15.250	2.7499	3.76	0.9766
5	18.0	15.948	2.0521	2.63	0.9278
6	18.0	15.948	2.0521	2.63	0.9278
23	11.0	9.3335	1.6665	3.71	0.9756
24	11.0	9.0531	1.9469	4.74	0.9912
25	10.0	8.9615	1.0385	2.40	0.9093
52	7.0	6.3738	0.6262	2.11	0.8792
53	7.0	6.3738	0.6262	2.11	0.8792
54	7.0	6.3738	0.6262	2.11	0.8792
76	3.0	2.7383	0.2618	2.07	0.8742
77	3.0	2.7383	0.2618	2.07	0.8742
78	3.0	2.7383	0.2618	2.07	0.8742
79	3.0	2.7383	0.2618	2.07	0.8742
80	3.0	2.7383	0.2618	2.07	0.8742
81	3.0	2.6831	0.3169	2.44	0.9127
82	3.0	2.6559	0.3440	2.64	0.9289

83	3.0	2.6291	0.3709	2.87	0.9432
84	3.0	2.6291	0.3709	2.87	0.9432
85	3.0	2.6291	0.3709	2.87	0.9432
101	1.0	2.4735	-1.4735	0.00	0.0007
102	1.0	2.4237	-1.4237	0.00	0.0009

The table presents unusual residuals for time in a Weibull regression analysis. Notably, in rows 3, 4, and 5, the model predicts significantly higher values than observed (19.0 predicted as 31.7096, yielding a large negative residual of -12.7096). Rows 4 to 6 show consistently underestimated observed values (18.0) compared to predictions around 15.25 to 15.95, with high standardized and Cox-Snell residuals indicating substantial deviations. Rows 23 to 25 similarly exhibit positive residuals, indicating underestimation of observed values around 11.0. Rows 52 to 85 demonstrate smaller positive residuals, suggesting moderate deviations from predicted values of 7.0. Rows 101 and 102 show negative residuals, suggesting overestimation of observed values (1.0). These residuals provide insights into points where the model's predictions diverge significantly from actual data, highlighting areas for potential model refinement or further investigation.

Table 3: Unusual Residuals for time of the Loglogistic Regression Models

Row	*Y*	*Predicted Y*	*Residual*	*Standardized Residual*	*Cox-Snell Residual*
1	26	23.889	2.1105	2.8200	0.7379
4	18	9.0717	8.9283	4350.5	0.9998
5	18	16.170	1.8300	3.7100	0.7877
6	18	16.170	1.8300	3.7100	0.7877
16	12	11.154	0.8464	2.4500	0.7098
17	12	11.154	0.8464	2.4500	0.7098
18	12	11.154	0.8464	2.4500	0.7098
23	11	9.2159	1.7842	8.7000	0.8970
24	11	8.8563	2.1437	14.160	0.9340
25	10	8.7396	1.2604	5.1900	0.8385
43	8	7.5531	0.4469	2.0200	0.6688
50	7	6.2387	0.7613	4.0900	0.8034
51	7	6.2387	0.7613	4.0900	0.8034
52	7	6.1565	0.8435	4.8100	0.8278
53	7	6.1565	0.8435	4.8100	0.8278
54	7	6.1565	0.8435	4.8100	0.8278
71	4	3.7645	0.2355	2.1000	0.6774
75	3	2.4256	0.5744	13.450	0.9308
76	3	2.3936	0.6064	15.820	0.9405
77	3	2.3936	0.6064	15.820	0.9405
78	3	2.3936	0.6064	15.820	0.9405
79	3	2.3936	0.6064	15.820	0.9405

Table 3 presents unusual residuals for the Time variable in the Loglogistic Regression Models. Each row corresponds to specific observations with their actual value (Y), predicted value (Predicted Y), residual (difference between Y and Predicted Y), standardized residual (residual divided by its standard deviation), and Cox-Snell residual (a type of transformation of residuals used in survival analysis). Key observations include row 4, where the residual and standardized residual are exceptionally large, indicating a significant deviation between observed and predicted values. Rows 23 to 79 also show higher-than-usual standardized residuals, suggesting these observations may have a notable impact on the model's fit or merit further investigation.

Tables 2 and 3 present unusual residuals for the Time variable in Weibull and Loglogistic regression models, respectively. In Table 2, instances include overestimation (e.g., predicted 31.7096 versus observed 19.0) and underestimation (e.g., predicted around 15.25 to 15.95 versus observed 18.0), with high standardized and Cox-Snell residuals indicating significant deviations. Rows 23 to 25 show underestimation around 11.0. Table 3 reveals discrepancies in the Loglogistic model, notably in row 4 with exceptionally large residuals, and rows 23 to 79 showing higher-than-usual standardized residuals, suggesting areas for further investigation. Overall, the Loglogistic model exhibits fewer large residuals and better fit statistics (lower AIC and BIC), suggesting it provides a more accurate representation and predictive performance compared to the Weibull model.

Table 4: Inverse Predictions for time of Weibull and Loglogistic Regression Models

Percent	Weibull Regression Model				Loglogistic Regression Model			
	Percentile	SE	Lower 95% C.L	Upper 95% C.L	Percentile	SE	Lower 95% C.L	Upper 95% C.L
0.1	0.5241	0.0653	0.4106	0.6689	0.7571	0.0864	0.6053	0.9469
0.5	0.6414	0.0739	0.5117	0.8041	0.8639	0.0946	0.6971	1.0706
1.0	0.6999	0.0783	0.5621	0.8714	0.9146	0.0985	0.7405	1.1297
2.0	0.7639	0.0831	0.6173	0.9453	0.9688	0.1029	0.7867	1.1929
3.0	0.8042	0.0861	0.6520	0.9919	1.0023	0.1056	0.8153	1.2322
4.0	0.8343	0.0884	0.6779	1.0268	1.0270	0.1077	0.8363	1.2613
5.0	0.8585	0.0903	0.6987	1.0549	1.0468	0.1093	0.8531	1.2846
6.0	0.8789	0.0918	0.7162	1.0787	1.0635	0.1107	0.8672	1.3042
7.0	0.8967	0.0932	0.7314	1.0994	1.0779	0.1119	0.8794	1.3213
8.0	0.9124	0.0945	0.7449	1.1177	1.0907	0.1130	0.8902	1.3364
9.0	0.9266	0.0956	0.7570	1.1343	1.1023	0.1141	0.8999	1.3501
10.0	0.9396	0.0966	0.7681	1.1494	1.1128	0.1149	0.9088	1.3626
15.0	0.9921	0.1009	0.8128	1.2108	1.1557	0.1187	0.9449	1.4135
20.0	1.0323	0.1042	0.8469	1.2581	1.1891	0.1217	0.9729	1.4534
25.0	1.0657	0.1070	0.8752	1.2975	1.2174	0.1243	0.9966	1.4872
30.0	1.0948	0.1095	0.8998	1.3319	1.2427	0.1267	1.0177	1.5175
35.0	1.1209	0.1118	0.9219	1.3630	1.2661	0.1289	1.0371	1.5456
40.0	1.1452	0.1139	0.9423	1.3918	1.2884	0.1309	1.0557	1.5725
45.0	1.1679	0.1159	0.9614	1.4189	1.3102	0.1331	1.0737	1.5988
50.0	1.1899	0.1179	0.9797	1.4451	1.3319	0.1352	1.0916	1.6249
55.0	1.2112	0.1199	0.9975	1.4705	1.3539	0.1373	1.1098	1.6517
60.0	1.2322	0.1219	1.0151	1.4958	1.3768	0.1396	1.1286	1.6795
65.0	1.2534	0.1238	1.0328	1.5212	1.4010	0.1420	1.1486	1.7090
70.0	1.2751	0.1259	1.0508	1.5473	1.4274	0.1447	1.1702	1.7412
75.0	1.2979	0.1281	1.0697	1.5748	1.4571	0.1478	1.1944	1.7775
80.0	1.3224	0.1304	1.0899	1.6044	1.4918	0.1514	1.2227	1.8201

85.0	1.3499	0.1331	1.1127	1.6377	1.5349	0.1560	1.2576	1.8732
90.0	1.3831	0.1364	1.1399	1.6780	1.5941	0.1625	1.3054	1.9465
91.0	1.3909	0.1372	1.1464	1.6875	1.6093	0.1642	1.3177	1.9655
92.0	1.3992	0.1380	1.1532	1.6977	1.6263	0.1661	1.3314	1.9867
93.0	1.4083	0.1389	1.1607	1.7087	1.6457	0.1682	1.3469	2.0107
94.0	1.4183	0.1399	1.1688	1.7209	1.6679	0.1708	1.3647	2.0386
95.0	1.4295	0.1411	1.1780	1.7346	1.6945	0.1738	1.3859	2.0718
96.0	1.4424	0.1424	1.1886	1.7504	1.7272	0.1776	1.4119	2.1129
97.0	1.4579	0.1440	1.2013	1.7695	1.7698	0.1826	1.4457	2.1666
98.0	1.4781	0.1461	1.2177	1.7942	1.8310	0.1900	1.4940	2.2440
99.0	1.5086	0.1494	1.2425	1.8317	1.9394	0.2035	1.5789	2.3822
99.5	1.5354	0.1522	1.2642	1.8647	2.0534	0.2182	1.6674	2.5288
99.9	1.5873	0.1579	1.3062	1.9289	2.3431	0.2579	1.8883	2.9074

Table 4 presents inverse predictions for the Time variable in both Weibull and Loglogistic regression models across various percentiles. For the Weibull regression model, percentiles from 0.1% to 99.9% exhibit predicted values ranging from 0.5241 to 1.5873, with corresponding standard errors (SE) and confidence intervals (95% C.L.) provided. Similarly, the Loglogistic regression model shows predictions from 0.7571 to 2.3431 across the same percentiles. Generally, both models indicate an increase in predicted values as percentiles rise, with the Loglogistic model consistently yielding higher predictions compared to the Weibull model across most percentiles. This suggests that the Loglogistic regression model may better capture higher percentiles and variability in the Time variable, indicating its potential superiority in predictive accuracy for this dataset.

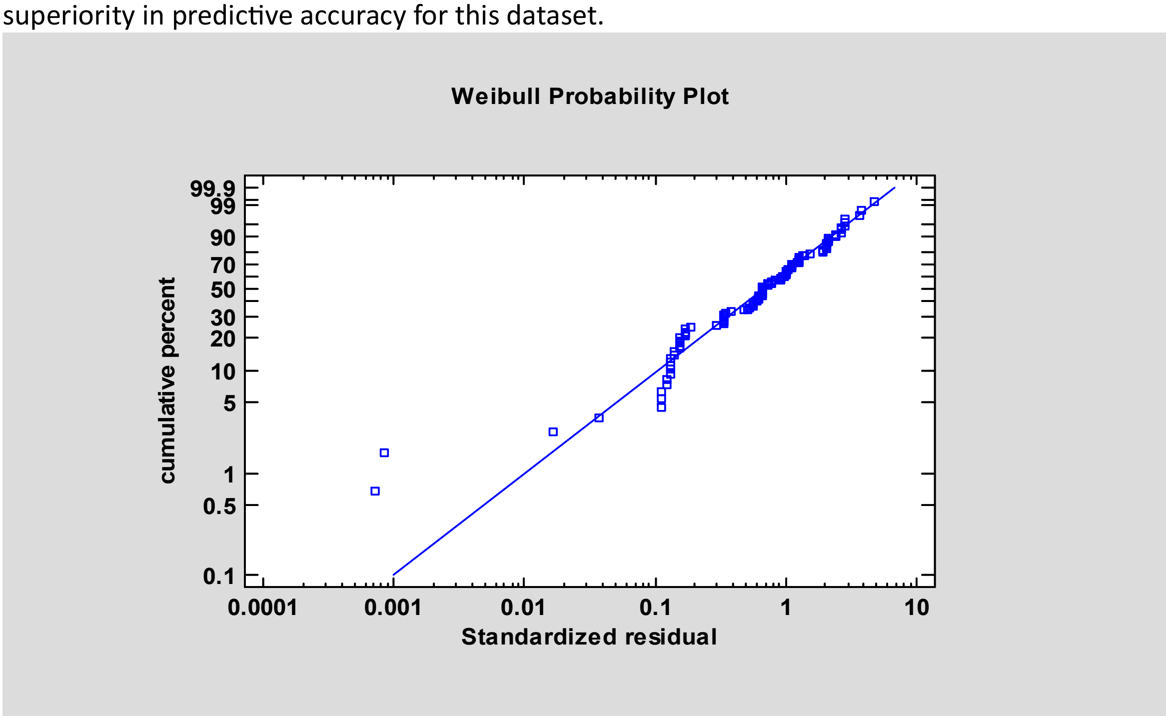

Figure 1: Weibull Probability Plot

Figure 1 is a graphical presentation which was used to assess how well data fits the Weibull distribution. The plotted data points shows that it follows Weibull distribution because the points fall approximately along a straight line.

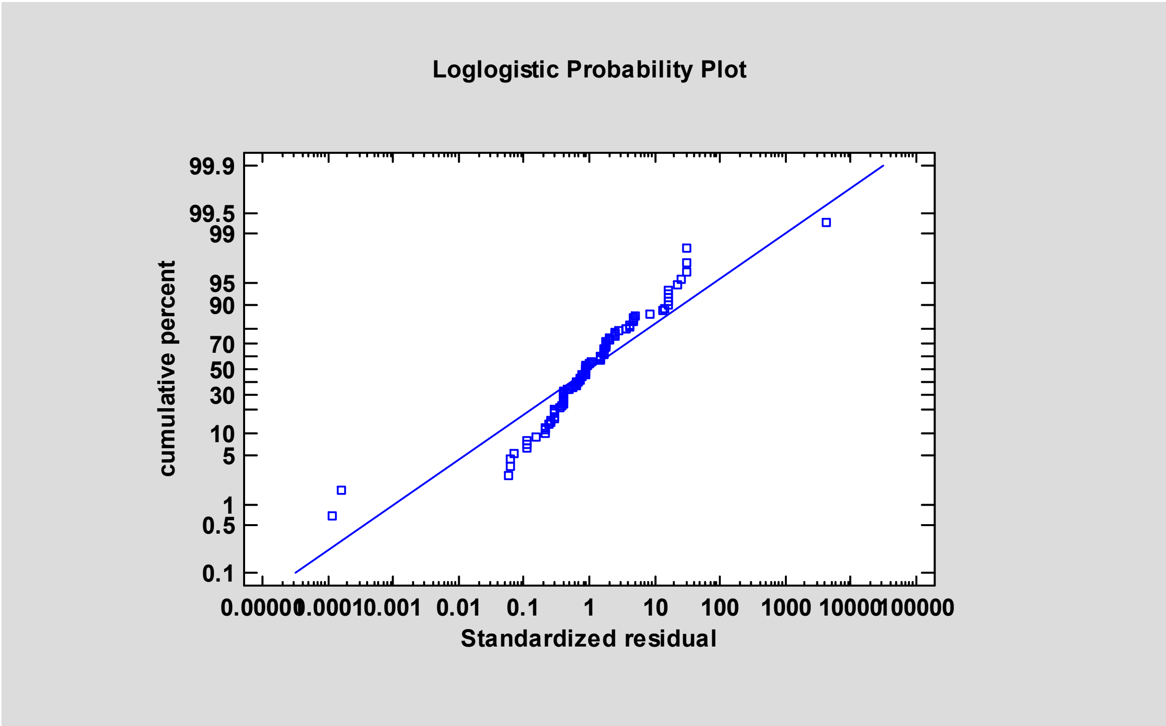

Figure 2: Loglogistic Probability Plot

Figure 2 is a graphical presentation which was used to assess how well data fits the Loglogistic distribution. The plotted data points shows that it follows Weibull distribution because the points fall approximately along a straight line.

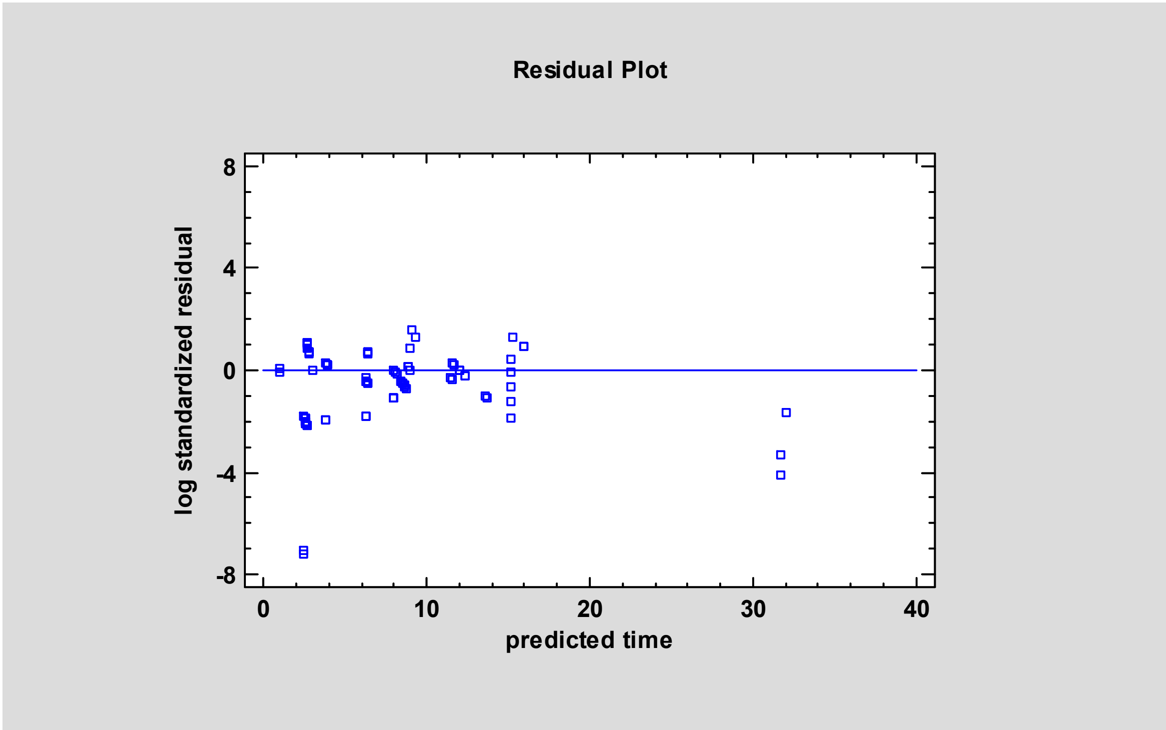

Figure 3: Residual plot of Weibull Regression Model

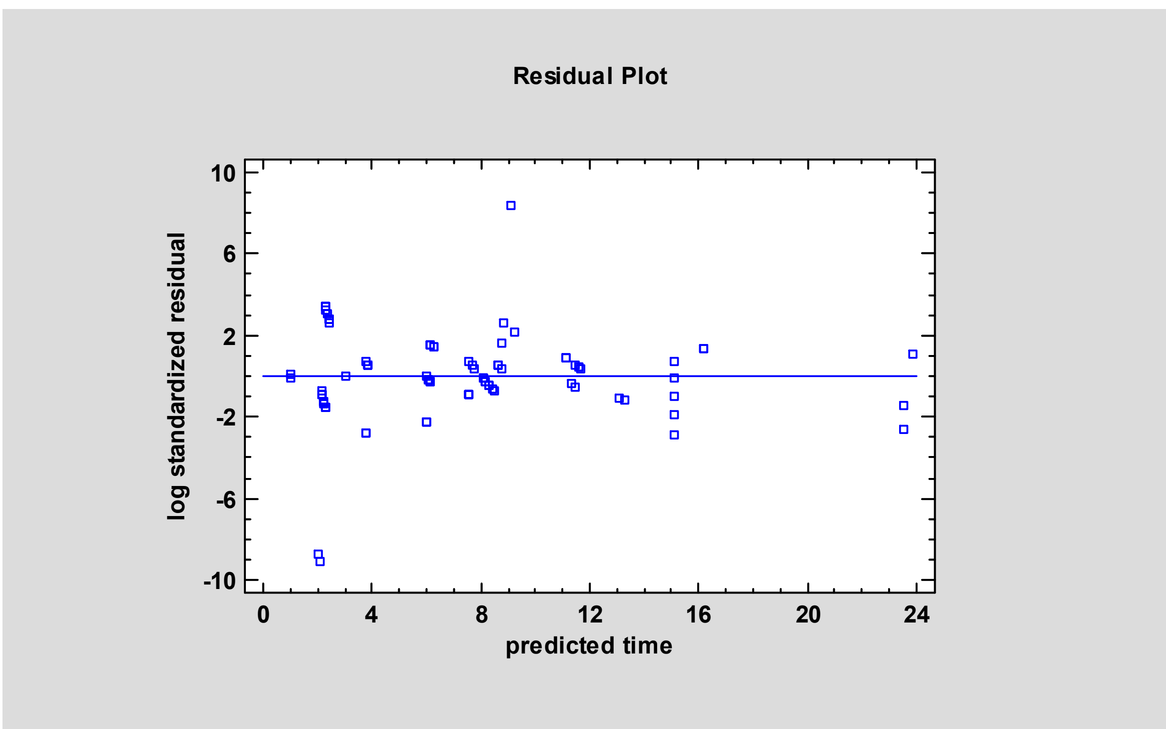

Figure 4: Residual plot of Loglogistic Regression Model

Figure shows that, the residuals plot of the Weibull and Loglogistic Regression analysis are randomly scattered around zero suggesting that the models fits the data well. This random scatter indicates that there is no systematic bias in the model's predictions across the entire range of predicted time to failure. It also implies that the models effectively captures the relationship between the predictor variables and the time to failure in the dataset without significant underlying trends or patterns in the residuals that would indicate consistent overestimation or underestimation at specific points.

Conclusion

In this comparative study of Weibull and Loglogistic regression models aimed at predicting Length of Stay (LOS) in the Emergency Department (ED) of General Hospital Damatu, Yobe State, Nigeria, rigorous statistical evaluation yielded valuable insights. The Weibull model demonstrated stronger associations with factors such as Age, Gender, and ED Crowding. However, it ultimately exhibited higher Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores relative to the Loglogistic model. Specifically, the Loglogistic regression model achieved lower AIC (155.05) and BIC (199.22) scores, indicating superior model fit and parsimony. It consistently outperformed the Weibull model in terms of log-likelihood (-68.527 vs. -83.459) and exhibited fewer instances of unusual residuals, highlighting its capability to offer a more precise estimation of LOS within the ED setting.

Moreover, likelihood ratio tests affirmed the statistical significance of both models across various predictive factors, highlighting Age, Gender, Time of Arrival, and Previous ED Visits as influential in LOS determination. While both models effectively captured these variables, the Loglogistic model's higher predictive accuracy, as evidenced by inverse predictions across percentile ranges, underscores its suitability for handling the complexities and variability inherent in ED patient stays. These findings not only contribute to advancing predictive modeling in healthcare settings but also offer actionable insights for hospital administrators and policymakers aiming to enhance resource allocation and patient management strategies in EDs.

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