



Research Article

Predicting Hospital Length of Stay (LOS) of Patients in the  
Emergency Department of Yobe State Hospitals Using A Weibull  
Regression Model

<sup>1</sup>Mohammed Audu and <sup>2</sup>Usman Muhammad Godowoli

<sup>1,2</sup>Department of Statistics, Yobe State College of Agricultural Science and Technology, Gajba

\*Corresponding author's Email: [jajere306@gmail.com](mailto:jajere306@gmail.com), [doi.org/10.55639/607.02010011](https://doi.org/10.55639/607.02010011)

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ABSTRACT

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This study aims to predict the Hospital Length of Stay (LOS) for patients in the Emergency Departments (ED) of General Hospital Damaturu using the Weibull Regression Model. LOS is a critical metric for hospital performance, and accurate prediction can optimize resource allocation, reduce costs, and enhance healthcare efficiency. A retrospective analysis of patients admitted to the ED of General Hospital Damaturu from January 2022 to December 2023 was conducted, considering variables such as Age (Chi-Square = 30.8531, df = 1, p < 0.0001), Gender (Chi-Square = 36.7738, df = 1, p < 0.0001), Time of Arrival (Chi-Square = 11.4658, df = 1, p = 0.0007), Previous Emergency Unit (Chi-Square = 42.9153, df = 1, p < 0.0001), Availability of Inpatient Bed (Chi-Square = 19.6701, df = 1, p < 0.0001), and Emergency Department Crowding (Chi-Square = 22.5123, df = 1, p < 0.0001) were found to be statistically significant predictors of length of stay (LOS) while abnormal vital signs, previous medical history, and laboratory tests were not significant. Cox Snell residual was used to investigate whether the model fits the data and the result showed that, it generally support the model fit, with most values close to zero.

**Corresponding author:** Mohammed Audu, **Email:** [jajere306@gmail.com](mailto:jajere306@gmail.com)

Department of Statistics, Yobe State College of Agricultural Science and Technology, Gajba

**INTRODUCTION**

The Length of Stay (LOS) is defined as the duration a patient spends hospitalized, measured in days (Han *et al.*, 2022). It stands out as a crucial metric in evaluating hospital performance, with a shorter stay having the

potential to reduce per-discharge costs and transition care to more cost-effective post-acute settings. Additionally, it can lead to a more efficient allocation of resources, a higher readmission rate, and improved overall service efficiency. As a tangible parameter, LOS is

instrumental in gauging the utilization of healthcare resources, highlighting its significance in health resource management (Burgess *et al.*, 2022).

The prediction of LOS for inpatients is a challenging yet essential undertaking for ensuring the operational success of a hospital. With hospitals grappling with limited resources, the ability to forecast LOS becomes invaluable for administrators in planning and managing resources effectively (Schneider *et al.*, 2021). LOS serves as a critical measure of healthcare utilization and a determinant of hospitalization costs, aligning with the overarching interest in controlling healthcare expenses. Despite the challenges, predicting LOS is crucial for resource planning, especially in the face of increasing clinical data generated through clinical trials, electronic patient records, and computer-supported disease management (Fink *et al.*, 2020).

The ability to reasonably predict the length of stay (LOS) for patients admitted from the emergency department is important in determining and managing healthcare resources. To optimize and effectively address patient care, consistent discrepancies between predicted and actual LOS may strain resources and cause consequences that can burden both the patient and the hospital (1). Admittedly, determining LOS with high accuracy is difficult as estimates are compounded by multiple variables such as patient care, insurance, and morbidity, all of which can influence LOS. Previous efforts have been made to quantify predicted LOS and compare it with the actual patient LOS in specific types of cases such as surgery and trauma. These cases, however, tend to have proven and well-studied protocols and neural networks that dictate patient flow during admittance while also predicting LOS (2). Psychiatry also has extensive literature documenting LOS prediction. Data from the psychiatric literature have shown that certain variables available during patient admittance can be assessed to predict patient LOS (3).

According to Kim and Lee (2022), the intricacies of managing patient flow within hospital Emergency Departments (ED) represent a significant challenge in contemporary healthcare settings. One key determinant of this

challenge is the variable length of stay (LOS) experienced by patients in the ED, reflecting the complexity and diversity of medical conditions presented. The unpredictable nature of ED admissions necessitates a comprehensive understanding of the factors influencing the duration of patient stays to optimize resource allocation and enhance the efficiency of healthcare delivery (Lucero *et al.*, 2021). The existing body of literature acknowledges the complex nature of ED operations and recognizes the need for sophisticated modeling techniques to predict and manage patient LOS (Rizk *et al.*, 2021). Weibull Regression analysis emerges as valuable statistical tools in this context, offering the capacity to interpret the diverse set of variables contributing to LOS variations.

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

The Length of Stay (LOS) for patients in healthcare facilities is influenced by diverse factors, presenting challenges in resource management and patient flow. LOS prediction is critical for optimizing resource utilization, improving healthcare service quality, and managing costs effectively. It serves as 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 have shown significant potential in achieving precise predictions across different healthcare settings, highlighting the importance of 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).

Therefore, this study endeavors to address key statistical challenges in predicting the Length of Stay (LOS) of patients in Emergency Departments of General Hospital Damaturu, employing Weibull Regression as the primary statistical tool. Firstly, the research seeks to unravel the intricate distributional patterns inherent in LOS data, leveraging the unique capabilities of Weibull Regression to capture and interpret these patterns. The Weibull Regression model is selected for its suitability in modeling time-to-event data and its flexibility in handling complex survival distributions.

Secondly, the study recognizes the multifactorial nature of variables influencing LOS and aims to identify and assess their significance within the Weibull Regression framework. The statistical challenge lies in developing precise risk stratification models using Weibull Regression, which can effectively categorize patients based on their LOS probabilities. Additionally, the study emphasizes the need for clear interpretation of the Weibull Regression model parameters, facilitating effective communication of findings to healthcare providers and administrators.

Moreover, the integration of the Weibull Regression model into the clinical workflow of Emergency Departments poses a unique statistical challenge. The study aims to collaborate with healthcare professionals to seamlessly implement the Weibull Regression model, ensuring practical and efficient utilization within real-world healthcare settings. By addressing these challenges, the research aims to contribute valuable insights to the prediction of LOS in Emergency Departments, leveraging the strengths of Weibull Regression for a more robust and comprehensive analysis. It is against this background that this study aims of the study is to predict hospital length of stay among patients in emergency department in General Hospital Damaturu, Yobe State.

## METHODOLOGY

This retrospective study included patients admitted to the Emergency Department (ED) of General Hospital Damatu both in Yobe State, Nigeria between January 2022 and December, 2023. Patient will be included if they were admitted to the hospital through the ED and stayed for more than two days for the subsequent hospital ward. Patients not admitted through the ED and patients with very short subsequent hospital stays (< 2 days) will be excluded. Excluding patients who stay for less than two days ensures consistency and relevance of data, as short stays may not provide sufficient information for accurate assessment and modeling of patient outcomes or resource utilization. The study focuses on patients requiring significant medical intervention, which is more likely for those with longer stays, thereby reducing variability and noise in the data and making it easier to identify patterns and draw meaningful conclusions. Additionally, patients with longer stays utilize a wider range of hospital resources and services, making the analysis more pertinent for hospital resource management. Aligning with the study's objectives, which likely focus on understanding factors influencing longer hospital stays, patient outcomes, and resource utilization, the minimum stay threshold helps maintain the study's focus and ensures that the data collected is relevant and consistent. The time spent in the Short Stay Emergency Ward will be accounted for in the total LOS. Patient stays and related features will be selected and extracted. The information to be used for modelling will be all information that will be available to the ED staff at the time of the patient's transfer to another ward of the hospital. This information will included: personal information such as (age, gender and medical history), context information such as entry date, LOS at the ED were collected and used. Data collected were analyzed using Weibull regression model. Weibull regression is chosen for the analysis due to its flexibility in modeling different hazard functions over time, its ability to handle censored data common in medical studies, and its suitability for survival analysis of time-to-event data like hospital length of stay. The model's parameters offer straightforward interpretations, and it allows for

the inclusion of covariates to compare different patient groups. These strengths make Weibull regression a powerful and versatile tool for deriving meaningful insights from the data in the study.

### 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 ( $x_9$ ).

**Functional Form:** The Weibull Regression model will be employed due to its suitability for modeling time-to-event data, which aligns with the nature of LOS.

### The Weibull Distribution

Let  $x_1, x_2, \dots, x_n$  be a random variable following a Weibull distribution, the cumulative distribution function (cdf) of the random variable  $X$  is defined by:

$$F(t; \alpha, \lambda) = 1 - \exp\left[-\left(\frac{t}{\lambda}\right)^\alpha\right], t, \lambda, \alpha \quad (1)$$

$F(t)$  = Cumulative distribution function (cdf)

$t$  = Length stay

$\lambda$  = The scale parameter that represents the characteristic time unit

$\alpha$  = The shape parameter that affects the shape of the hazard function

The survival function corresponding to equation (2) is given by:

$$S(t) = 1 - F(t) = \exp\left[-\left(\frac{t}{\lambda}\right)^\alpha\right] \quad (2)$$

and the corresponding hazard function is also given by:

$$h(t) = \frac{\alpha}{\lambda^\alpha} t^{\alpha-1} \quad (3)$$

### Weibull Regression Model

The Weibull regression model is a regression model derived from the Weibull distribution with the lambda ( $\lambda$ ) parameter expressed in terms of the regression parameters and given by the following relationship:

$$\ln \lambda = \beta^T X = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p \quad (4)$$

Where  $\lambda = \exp(\beta^T X)$  and  $\beta^T = [\beta_0, \beta_1, \dots, \beta_p]$  is a regression parameter vector of dimension  $p + 1$ .

$\beta_0$  = The intercept

$\beta_i$  = Are the regression coefficient for each covariate  $x_i$

$x_1$  = Age of patient

$x_2$  = Gender

$x_3$  = Abnormal vital sign

$x_4$  = Time of arrival

$x_5$  = Previous medical history

$x_6$  = Previous emergency unit

$x_7$  = Availability of inpatient bed

$x_8$  = Emergency department crowding

### Model Specification

#### Dependent Variable

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

$x_9$  = Laboratory test

$\sigma$  = The scale parameter that affects the overall rate of the process

$\varepsilon$  = Error term with an extreme minimum value distribution

The hazard rate function at time  $t$  is given by:

$$h(t|X) = \lambda \alpha t^{\alpha-1} \exp(\beta' X)$$

where  $h(t|X)$  is the hazard function at time  $t$ ,  $\lambda$  is the scale parameter,  $\alpha$  is the shape parameter,

$\beta$  is the vector of coefficients, and  $X$  represents the covariates.

## RESULTS

**Table 1: Likelihood Ratio Tests**

Factor	Chi-Square	df	p-value
Age	30.8531	1	0.0000
Gender	36.7738	1	0.0000
Abnormal Vital Sign	0.11343	1	0.7363
Time of Arrival	11.4658	1	0.0007
Previous Medical History	2.11844	1	0.1455
Previous Emergency Unit	42.9153	1	0.0000
Availability of Inpatient Bed	19.6701	1	0.0000
Emergency Department Crowding	22.5123	1	0.0000
Laboratory Test	0.49725	1	0.4807

Table 1 provide the likelihood ratio tests for the factors in the Weibull regression model. The results indicated significant associations for several predictors. Age (Chi-Square = 30.8531, df = 1,  $p < 0.0001$ ), Gender (Chi-Square = 36.7738, df = 1,  $p < 0.0001$ ), Time of Arrival (Chi-Square = 11.4658, df = 1,  $p = 0.0007$ ), Previous Emergency Unit (Chi-Square = 42.9153, df = 1,  $p < 0.0001$ ), Availability of Inpatient Bed (Chi-Square = 19.6701, df = 1,  $p < 0.0001$ ), and Emergency Department Crowding (Chi-Square = 22.5123, df = 1,  $p < 0.0001$ ) all show statistically significant effects on the hazard rate. This implies that, the factors are determinants of LOS. Factors such as Abnormal

Vital Sign (Chi-Square = 0.113431, df = 1,  $p = 0.7363$ ), Previous Medical History (Chi-Square = 2.11844, df = 1,  $p = 0.1455$ ), and Laboratory Test (Chi-Square = 0.497251, df = 1,  $p = 0.4807$ ) do not exhibit statistically significant associations. This implies that, those factors are not significant predictors of Hospital LOS. These results suggest that age, gender, time of arrival, previous emergency unit visits, availability of inpatient beds, and emergency department crowding significantly influence the hazard rate in the Weibull regression model, while abnormal vital signs, previous medical history, and laboratory tests do not.

**Table 2:** Unusual Residuals for Time

<i>Row</i>	<i>Y</i>	<i>Predicted Y</i>	<i>Residual</i>	<i>Standardized Residual</i>	<i>Cox-Snell Residual</i>
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	-1.47353	0.00	0.0007
102	1.0	2.4237	-1.42374	0.00	0.0009

Table 2 presents unusual residuals for time in a Weibull regression analysis. 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 information on the points where the model's predictions diverge significantly from actual data.

Therefore, the residual analysis reveals the fit of the model to individual observations. Standardized residuals close to zero indicate a good fit, while larger absolute values suggest poor fit or potential outliers. The large residuals include Row 24 with a standardized residual of 4.74, indicating a poorly fitted observation. In other hand, Row 3 has a standardized residual of 0.02, showing a well-fitted observation. Cox-Snell residuals generally support the model fit, with most values close to zero.

**Table 3:** Inverse Predictions for time

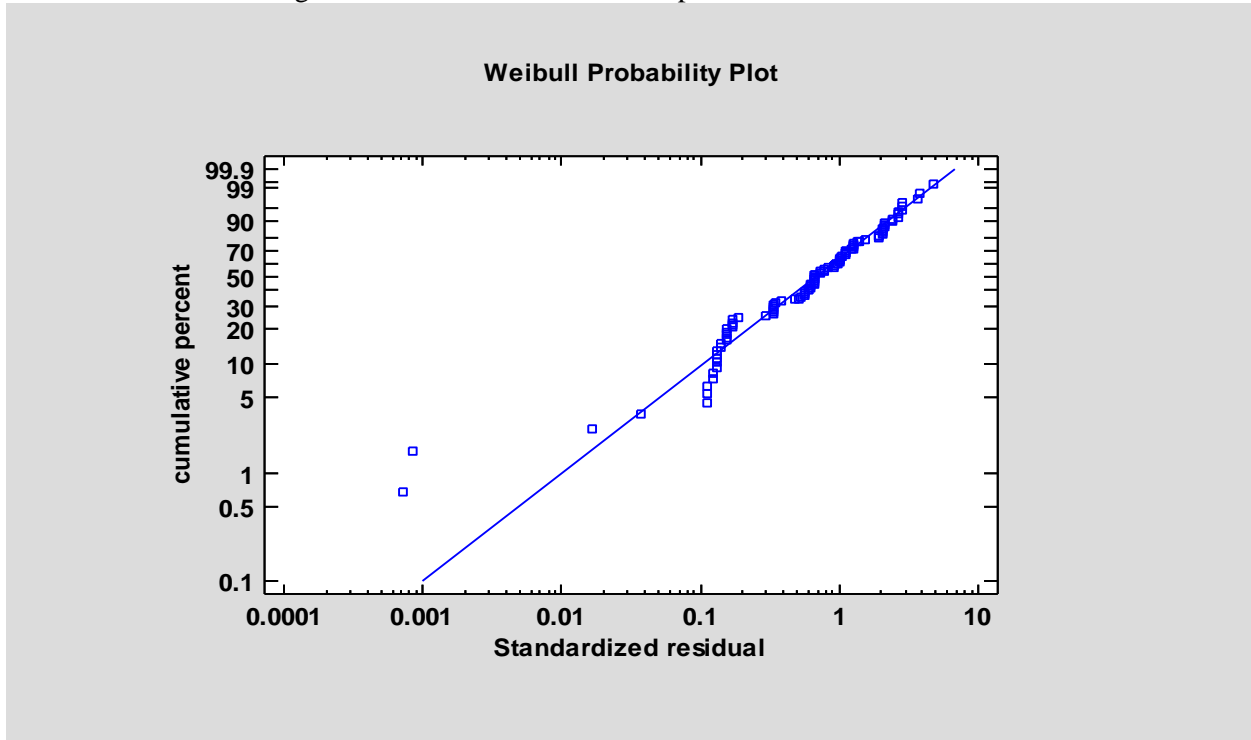
<i>Percent</i>	<i>Percentile</i>	<i>Standard Error</i>	<i>Lower 95.0% Conf. Limit</i>	<i>Upper 95.0% Conf. Limit</i>
0.1	0.52411	0.06525	0.41063	0.66896
0.5	0.64143	0.07397	0.51166	0.80411
1.0	0.69987	0.07829	0.56209	0.87143
2.0	0.76389	0.08305	0.61728	0.94531
3.0	0.80423	0.08609	0.65202	0.99197
4.0	0.83429	0.08838	0.67787	1.02682
5.0	0.85852	0.09025	0.69867	1.05495
6.0	0.87895	0.09183	0.71619	1.07869
7.0	0.89669	0.09322	0.73139	1.09935
8.0	0.91244	0.09446	0.74487	1.11770
9.0	0.92663	0.09559	0.75701	1.13427
10.0	0.93959	0.09662	0.76808	1.14941
15.0	0.99205	0.10088	0.81279	1.21084
20.0	1.03226	0.10421	0.84695	1.25813
25.0	1.06566	0.10703	0.87524	1.29752
30.0	1.09477	0.10953	0.89983	1.33195
35.0	1.12099	0.11182	0.92192	1.36303
40.0	1.14519	0.11395	0.94228	1.39180
45.0	1.16799	0.11599	0.96142	1.41896
50.0	1.18985	0.11796	0.97973	1.44505
55.0	1.21115	0.11991	0.99753	1.47051
60.0	1.23222	0.12185	1.01510	1.49576
65.0	1.25341	0.12383	1.03275	1.52121
70.0	1.27512	0.12588	1.05080	1.54733
75.0	1.29786	0.12805	1.06965	1.57475
80.0	1.32237	0.13042	1.08993	1.60437
85.0	1.34991	0.13312	1.11267	1.63773
90.0	1.38309	0.13641	1.13998	1.67804
91.0	1.39086	0.13719	1.14637	1.68751
92.0	1.39922	0.13803	1.15322	1.69768
93.0	1.40828	0.13895	1.16066	1.70873
94.0	1.41826	0.13996	1.16884	1.72092
95.0	1.42947	0.14111	1.17801	1.7346
96.0	1.44240	0.14244	1.18859	1.75042
97.0	1.45796	0.14404	1.20129	1.76947
98.0	1.47810	0.14614	1.21771	1.79417
99.0	1.50863	0.14936	1.24254	1.83171
99.5	1.53538	0.15222	1.26423	1.86468
99.9	1.58729	0.15786	1.30618	1.9289

Table 3 presents the inverse predictions for time at various percentiles, along with their corresponding standard errors and confidence intervals. The 50th percentile (median), the predicted time is 1.18985 with a standard error of 0.117963, and the 95% confidence interval

ranges from 0.979725 to 1.44505. As the percentile increases, so does the predicted time, with corresponding increases in standard error and the width of the confidence interval. At the 99.9th percentile, the predicted time is 1.58729, with a standard error of 0.157857, and the

confidence interval spans from 1.30618 to 1.9289. These values provide estimates of time based on the Weibull regression model across a

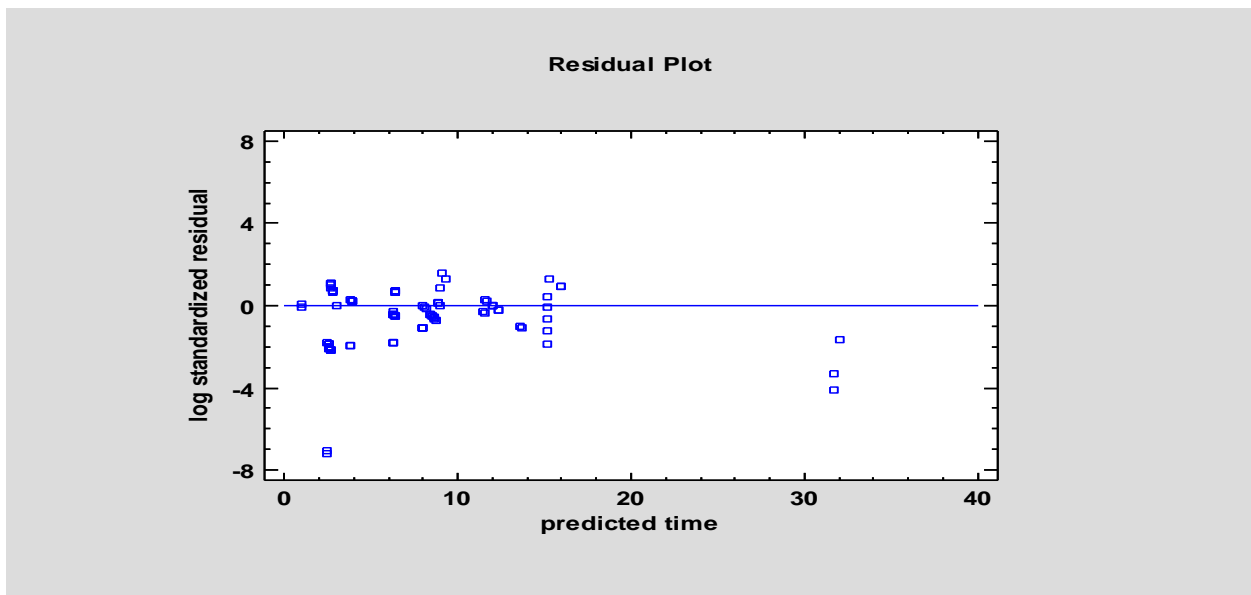
range of percentiles which gives insights into the distribution and uncertainty associated with predicted times.



**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

show that it follows Weibull distribution because the points fall approximately along a straight line.



**Figure 2:** Residual plot



Figure 2 shows that, the residuals plot of the Weibull Regression analysis are randomly scattered around zero suggesting that the model 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 model 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.

### DISCUSSION

The results of the Weibull regression analysis indicate that several factors, including age, gender, time of arrival, previous emergency unit visits, availability of inpatient beds, and emergency department crowding, significantly influence the hazard rate, highlighting their importance and providing valuable insights for healthcare practitioners and policymakers aiming to improve patient outcomes. Conversely, abnormal vital signs, previous medical history, and laboratory tests do not show significant associations, suggesting they may not be critical in predicting the timing of events in this analysis. The analysis of unusual residuals highlights specific points where the model's predictions diverge from actual data, indicating areas for potential refinement or further investigation. Overall, the model fits the

data well, as evidenced by the random scatter of residuals and the good fit to the Weibull distribution, providing a comprehensive understanding of the factors influencing the hazard rate and demonstrating the reliability of the Weibull regression model in capturing these relationships.

### CONCLUSION

Based on the Weibull regression analysis, the model appears to reasonably fit the data on time to failure. Key findings include the estimation of coefficients indicating how variables like age, gender, and emergency department crowding affect failure time, with statistically significant factors having a notable impact. A well-fitted model is indicated by residuals that scatter randomly around zero, suggesting it effectively captures the relationships between included factors and failure time. The Weibull probability plot shows data points generally align along a straight line, indicating adherence to a Weibull distribution, though deviations, particularly at extreme percentiles, suggest potential model limitations or underlying complexities in the failure process. While the model captures essential trends, opportunities for enhancement include conducting goodness-of-fit tests for formal evaluation, considering a balance between model complexity and accuracy, and investigating deviations in the probability plot to identify areas for further exploration or refinement.

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