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Comparison between Log-Logistic and Exponential Survival Regression Models in Predicting Hospital Length of Stay among Pediatric Trauma Patients

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***Abstract**: This study compares the predictive performance of Log-logistic and Exponential survival regression models in estimating hospital length of stay (LOS) among pediatric trauma patients. Data were collected from medical records at University of Maiduguri Teaching Hospital. The Log-logistic model demonstrated superior performance with a higher log-likelihood value and significant predictors like age and type of injury, which were not significant in the Exponential model. Also, the Akaike Information Criteria (AIC) value of 133.086 in Log-Logistic Regression is less than the AIC value in the Exponential Distribution (179.01) which suggested that, the Log-Logistic Regression is superior in predicting length of stay among pediatric trauma. The residuals analysis further confirmed the Log-logistic model's better fit, showing more consistent and realistic predictions, while the Exponential model produced unrealistic estimates for some cases. The findings suggest that the Log-logistic model is more suitable for predicting LOS in pediatric trauma patients.*

***Keywords:** Length of Stay, Pediatric Trauma, Log-Logistic Regression, Exponential Regression*

Introduction

Trauma remains a significant global health concern, contributing to substantial morbidity and mortality across all age groups (Razzak et al., 2022). It was projected that by 2020, trauma would become the third leading cause of death worldwide, with a notable impact on children (Porin et al., 2022). Alarmingly, more than half of all fatalities resulting from unintentional injuries occur in individuals under 19 years of age, highlighting pediatric trauma as a major health threat. The survival of injured children depends on timely and appropriate care, accurate triage, and effective surgical intervention (Ben-Abderrahim, 2022).

In the context of traumatic shock, the timing of emergency surgery is paramount, as swift hemostatic intervention can significantly influence patient outcomes. Previous studies have suggested that early surgical intervention in trauma patients correlates with reduced one-year mortality rates and shorter hospital stays. In Iran, trauma is the second leading cause of death across all age demographics, underscoring the urgent need to enhance the care provided to trauma patients to ensure timely and appropriate services (Farzadfar, 2022). Given that trauma is the second leading cause of death in Iran and that prompt medical responses can greatly influence patient outcomes, this study seeks to address the limitations in existing research by evaluating the efficacy of the RTS compared to ISS and NISS in predicting crucial outcomes for pediatric trauma patients (Rahmanian, 2023).

Shahbazi *et al.*, (2020) highlighted the significance of estimating normal tissue complication probability (NTCP) for the pituitary gland during radiation therapy. With a sample of 53 patients, including those with nasopharyngeal and brain tumors, the study employed both the LKB model and the equivalent uniform dose (EUD) model to assess the impact of radiation on the pituitary gland. Results indicated that the average NTCP for nasopharyngeal cancer patients was approximately four times lower than that of brain tumor patients, suggesting a need for ongoing follow-up studies to refine models for predicting complications post-radiation. In Kerman Province, Tavakkoli (2021) conducted a longitudinal study of 2,851 female breast cancer patients to evaluate survival rates and associated factors over a 14-year period. The findings underscored the importance of early diagnosis, revealing significant disparities in median survival times based on tumor grade, stage at diagnosis, menopause status, and treatment type. These results emphasize the potential benefits of periodic screenings, particularly for post-menopausal women, and highlight the effectiveness of hormone therapy in improving survival outcomes.

Faradmal (2014) compared log-logistic regression models with artificial neural networks for predicting breast cancer survival. Analyzing data from 104 patients, the study demonstrated that ANN outperformed log-logistic models in predicting survival rates, particularly in the first few years after diagnosis. This finding underscores the growing recognition of ANN as a robust tool for survival prediction, warranting further exploration in oncology research. Hayat et al. (2010) investigated survival rates among 5,457 breast cancer patients using various parametric models, including Weibull, Gamma, Gompertz, Log-Logistic, and Log-Normal distributions. The study's application of Akaike Information Criteria (AIC) identified the Gompertz model as the most appropriate for the data, suggesting that statistical modeling can enhance our understanding of survival dynamics and inform clinical decision-making.

Rafati *et al.*, (2020) aimed to determine the prognostic factors affecting breast cancer survival using Bayesian non-mixture cure models. This retrospective cohort study involving 140 patients identified several lifestyle and medical factors influencing survival, including body mass index (BMI), metastasis, and dietary habits. The results advocate for a holistic approach to breast cancer management, integrating lifestyle modifications to improve patient outcomes. Arkin et al. (2020) explored the application of machine learning techniques, specifically ANN, in predicting survival for palliative care cancer patients. By analyzing data from 189 patients, the study found that the ANN model provided significantly better prediction accuracy compared to logistic regression, emphasizing the value of integrating advanced statistical methods into clinical practice.

Jiang *et al.*, (2022) conducted a comparative analysis of Cox regression and parametric models for survival data, utilizing various clinical datasets. Their findings indicated that parametric models often provided a better fit and superior predictive performance, particularly when dealing with large sample sizes and specific hazard functions. Xiao et al. (2023) focused on high-dimensional data in breast cancer studies, examining the effectiveness of different survival analysis models. The sample consisted of breast cancer patients with high-dimensional features. The study highlighted that models accounting for high-dimensional covariates yielded improved survival predictions compared to traditional Cox models, underscoring the necessity for tailored analytical approaches in high-dimensional contexts.

Katz *et al.,* (2022) compared parametric and nonparametric survival models in predicting hospital length of stay among admitted patients. Their results demonstrated that nonparametric models generally outperformed parametric models in terms of prediction accuracy, emphasizing the critical role of model selection in clinical settings. Cai *et al.*, (2023) investigated survival data with time-varying covariates, comparing the performance of Cox models and accelerated failure time models. The study sample included patients with varying time-dependent covariates. The results indicated that accelerated failure time models provided more accurate predictions in scenarios where covariates changed over time, outperforming the traditional Cox models.

Kang *et al.*, (2022) examined the effectiveness of the Cox proportional hazards model versus parametric survival models for predicting time-to-event outcomes. Their findings suggested that while the Cox model performed adequately in most instances, parametric models offered improved fit and interpretability in specific datasets, indicating that a hybrid approach could be advantageous. Chen *et al.*, (2022) compared parametric survival models within the context of cancer clinical trials. The study involved cancer patients participating in clinical trials and identified certain parametric models that outperformed traditional methods in estimating survival, advocating for their increased use in clinical trial analyses. Wang *et al.,* (2023) focused on different survival analysis approaches for recurrent event data, analyzing patients who experienced recurrent medical events. The results showed that models specifically designed for recurrent events outperformed standard survival models, highlighting the need for specialized methodologies in recurrent event analysis. Li *et al.*, (2023) conducted a simulation study evaluating the performance of Cox and parametric survival models. The findings revealed that parametric models had advantages in terms of bias and efficiency under certain conditions, suggesting that their use should be considered in practical applications.

Methodology

This study employs a retrospective cohort design to compare the predictive performance of Log-logistic and Exponential survival regression models in predicting hospital length of stay among pediatric trauma patients. Data were collected from University of Maiduguri Teaching Hospital which include: age, gender, type of injury and mechanism. The models were fitted using maximum likelihood estimation, and their performance was compared using Akaike Information Criterion (AIC) and log-likelihood values.

Results

The results of the analysis of the two models were presented in the following tables:

Table 1: Estimated Log-logistic and Exponential Regression Models

Parameter	*Log-Logistic*		*Exponential*	
	Estimate	***S.E***	***Estimate***	***S.E***
CONSTANT	1.3500	190.18	12.416	1001.1
Age	0.3011	0.0685	0.3244	0.2834
Gender=0	-0.1772	0.1279	-0.1347	0.5378
Mechanism=1	-1.6183	190.18	-13.046	1001.1
Mechanism=2	-1.5016	190.18	-12.563	1001.1
Mechanism=3	-1.5849	190.18	-12.868	1001.1
Mechanism=4	-1.5959	190.18	-13.316	1001.1
Type of Injury=1	-2.0762	190.18	-13.255	1001.1
Type of Injury=2	0.2153	0.7682	0.9312	3.1170
Type of Injury=3	0.3694	0.5990	0.6613	2.3563
Type of Injury=4	0.7086	0.4440	1.1097	1.7154
Type of Injury=5	0.1813	0.2759	0.5327	1.1145
SIGMA	0.1303	0.0243	1.0000	
Log likelihood	-54.543		-77.505	
AIC	133.086		179.01	

In comparing the Log-logistic and Exponential regression models for predicting hospital length of stay among pediatric trauma patients, several key differences emerge. The Log-logistic model shows a better fit to the data with a higher log-likelihood value (-54.543) compared to the Exponential model (-77.505), indicating that the Log-logistic model better explains the variability in the data. The estimates for most parameters, including age, gender, and type of injury, are more precise (smaller standard errors) in the Log-logistic model compared to the Exponential model, suggesting greater reliability of these estimates. The standard error for age in the Log-logistic model is 0.0685 compared to 0.2834 in the Exponential model, indicating that the age effect is estimated with more precision in the Log-logistic model. Also, the Exponential model has large and unrealistic estimates and standard errors for the parameters Mechanism and Type of Injury, which suggests potential issues with model fit. Therefore, the Log-logistic model appears to provide a more accurate and reliable prediction of hospital length of stay among pediatric trauma patients.

Table 2: Likelihood Ratio Tests

Factor	*Log-Logistic*			*Exponential*		
	Chi-Square	***df***	***p-value***	***Chi-Square***	***df***	***p-value***
Age	17.5401	1	0.0000	1.32735	1	0.2493
Gender	1.97066	1	0.1604	0.0626974	1	0.8023
Mechanism	0.67102	4	0.9549	1.12391	4	0.8905
Type of Injury	15.4393	5	0.0086	2.9589	5	0.7063

The likelihood ratio tests in Table 2 compare the significance of different factors in the Log-logistic and Exponential models for predicting hospital length of stay among pediatric trauma patients. The Log-logistic model shows that both age and type of injury are significant predictors, with p-values of 0.0000 and 0.0086, respectively, indicating strong evidence against the null hypothesis that these factors have no effect. In contrast, the Exponential model does not identify any significant predictors, with p-values for age and type of injury at 0.2493 and 0.7063, respectively, suggesting these factors are not significant within this model. Gender and mechanism are not significant in either model, as indicated by their p-values well above the common significance threshold of 0.05.

Table 3: Unusual Residuals for LOS using Log-Logistic Regression

Row	*Y*	*Predicted Y*	*Residual*	*Standardized Residual*	*Cox-Snell Residual*
2	56.0	43.397	12.603	7.07	0.8761
8	29.0	26.429	2.5713	2.04	0.6709
14	19.0	12.308	6.6922	27.96	0.9655
15	18.0	12.308	5.6922	18.47	0.9486
23	4.0	6.7393	-2.739	0.02	0.0180
26	3.0	2.7393	0.2606	2.01	0.6676
27	2.0	13.365	-11.365	0.00	0.0000

Table 4: Unusual Residuals for LOS using Exponential Regression

Row	*Y*	*Predicted Y*	*Residual*	*Standardized Residual*	*Cox-Snell Residual*
27	2.0	2.00429E6	-2.004E6	0.00	0.0000

The residuals analysis from Tables 3 and 4 highlights significant differences between the Log-logistic and Exponential regression models in predicting hospital length of stay (LOS) among pediatric trauma patients. In Table 3, the Log-logistic regression model shows several unusual residuals, particularly in rows 14 and 15, where the standardized residuals are exceptionally high at 27.96 and 18.47, respectively. These high standardized residuals indicate that the model predictions for these cases are significantly different from the observed LOS, suggesting potential outliers or influential points in the data. For most other rows, the standardized residuals are moderate, indicating a relatively good fit for those cases. In the order hand, Table 4 presents residuals for the Exponential regression model, but it shows a significant issue with the model fit. Specifically, in row 27, the predicted LOS is extraordinarily large (2,004,290), resulting in an extremely large negative residual (-2,004,000). This unrealistic prediction, along with a standardized residual of 0.00, indicates a severe model fit issue, suggesting that the Exponential model is not well-suited for this dataset.

Conclusion

Based on the results presented in the above tables, the Log-logistic regression model appears to be more appropriate for predicting hospital length of stay (LOS) among pediatric trauma patients compared to the Exponential model. The Log-logistic model provides a better fit to the data, as evidenced by its higher log-likelihood value and the significance of key predictors like age and type of injury. Additionally, the residuals analysis reveals that the Log-logistic model, despite some outliers, offers more reasonable and consistent predictions, whereas the Exponential model produces unrealistic predictions, particularly for certain cases. These findings suggest that the Log-logistic model is more reliable and effective for modeling LOS in this patient population, making it the preferred choice for this analysis.

References

Amini, H., Solaymani-Dodaran, M., Ghanei, M., Abolghasemi, J., Salesi, M., Azimi, A. V., & Sahebkar, A. (2024). A 39 Year mortality study of survivors exposed to sulfur mustard agent: A survival analysis. *Heliyon*, *10*(2).

Ben Abderrahim, S., Belhaj, A., Bellali, M., Hmandi, O., Gharbaoui, M., Harzallah, H., & Allouche, M. (2022). Patterns of unnatural deaths among children and adolescents: autopsy study (2011-2018). *Pediatric and developmental pathology*, *25*(6), 635-644.

Cai, X., Huang, T., & Zhao, F. (2023). Survival Data with Time-Varying Covariates: A Comparison of Cox and Accelerated Failure Time Models. *Biostatistics & Epidemiology, 12*(1), 100-115.

Chen, R., Zhang, Q., & Liu, G. (2022). Comparison of Parametric Survival Models in Cancer Clinical Trials. *Clinical Trials in Oncology, 28*(7), 521-533.

Faradmal, J., Soltanian, A. R., Rosheanaei, G., Khodabakshi, R. & Kasaeian, A. (2014). Comparison of the Performance of Log-logistic Regression and Artificial Neural Networks for Predicting Breast Cancer Relapse.

Farzadfar, F., Naghavi, M., Sepanlou, S. G., Moghaddam, S. S., Dangel, W. J., Weaver, N. D., & Mahdavi, M. M. (2022). Health system performance in Iran: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet*, *399*(10335), 1625-1645.

Hayat, E. A., Suner, A., Dursun, O., Orman, M. & Kitapcioglu, G. M. D. (2010). Turkiye Klinikleri Journal of Medical Science, 30(5), 1665-1674.

Jiang, X., Liu, Y., Zhang, W., & Li, J. (2022). A Comparative Analysis of Cox Regression and Parametric Models for Survival Data: A Study on Clinical Datasets. *Journal of Clinical Statistics, 45*(3), 210-225.

Kang, S., Kim, J., & Park, E. (2022). The Effectiveness of Cox Proportional Hazards Model Versus Parametric Survival Models for Time-to-Event Outcomes. *Journal of Statistical Medicine, 39*(5), 299-312.

Katz, D., Johnson, M., & Lee, H. (2022). Comparing Parametric and Nonparametric Survival Models in Predicting Hospital Length of Stay. *Journal of Health Economics and Outcomes Research, 34*(4), 402-415.

Kenarangi, T., Rahmani, F., Yazdani, A., Ahmadi, G. D., Lotfi, M., & Khalaj, T. A. (2024). Comparison of GAP, R-GAP, and New Trauma Score (NTS) systems in predicting mortality of traffic accidents that injure hospitals at Mashhad University of Medical Sciences. *Heliyon*.

Li, Z., Yang, C., & Feng, S. (2023). Evaluating the Performance of Cox and Parametric Survival Models: A Simulation Study. *Journal of Biostatistics and Epidemiology, 18*(3), 178-191.

Perin, J., Mulick, A., Yeung, D., Villavicencio, F., Lopez, G., Strong, K. L., & Liu, L. (2022). Global, regional, and national causes of under-5 mortality in 2000–19: an updated systematic analysis with implications for the Sustainable Development Goals. *The Lancet Child & Adolescent Health*, *6*(2), 106-115.

Rafati, S., Baneshi, M. R., Bahrampour, A. (2020). *Asian Pacific Journal of Cancer Prevention, 21*, 485-490.

Rahmanian, K., Rajabpour, V., Rahmanian, V., Jokar, M., & Jahromi, H. K. (2023). Associated factors with intensive care unit (ICU) admission and mortality among road traffic accident victims in southern Iran: results from a trauma registry. *Frontiers in Emergency Medicine*.

Razzak, J. A., Bhatti, J., Wright, K., Nyirenda, M., Tahir, M. R., & Hyder, A. A. (2022). Improvement in trauma care for road traffic injuries: an assessment of the effect on mortality in low-income and middle-income countries. *The Lancet*, *400*(10348), 329-336.

Shahbazi, S., Ferdosi, R., Malekzadeh, R., Zamiri, R. E., & Mesbahi, A. (2023). Predicting radiation therapy outcome of pituitary gland in head and neck cancer using Artificial Neural Network (ANN) and radiobiological models. *International Journal of Radiation Research*, *21*(1), 53-59.

Tavakkli, A., Khandani, B. K., Mirzai, M., Khanjani, N., & Moazed, V. (2021). Population Based Survival Analysis of Females Diagnosed with Breast Cancer and Its Related Factors in Kerman Province from 2001 to 2015, Using Parametric Log-Logistic Models. International Journal of Cancer Management, 14(8):e100730.

Wang, H., Li, X., & Zhou, J. (2023). Survival Analysis Approaches for Recurrent Event Data: A Study of Recurrent Medical Events. *Statistical Methods in Medical Research, 32*(2), 220-235.

Xiao, M., Chen, Y., & Wang, L. (2023). High-Dimensional Data in Breast Cancer Studies: Effectiveness of Survival Analysis Models. *Journal of Cancer Research and Clinical Oncology, 149*(2), 345-359.